PREDICTING CRIME LEVELS WITH NYPD

CS 513 - B GROUP 22

OUR TEAM

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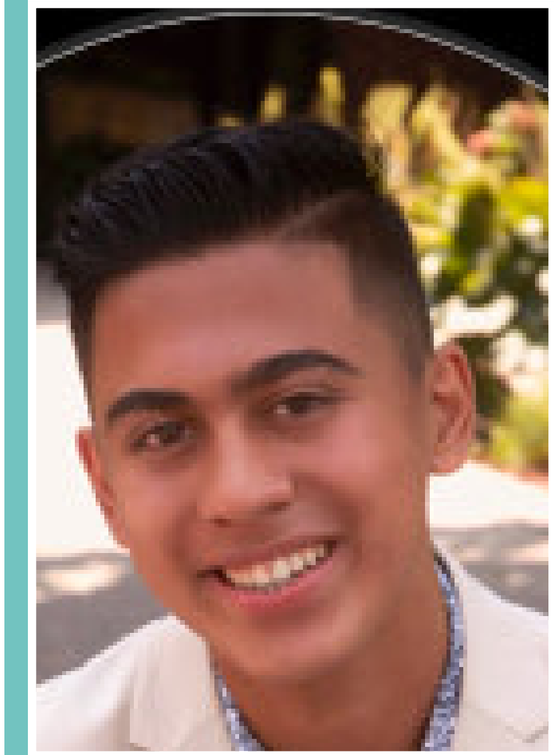

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CWID: 20014830

TOPICS TO COVER...

01 PROJECT MOTIVATION

02 EXPLORATORY DATA ANALYSIS

03 MODELS

04 CONCLUSIONS

PROJECT MOTIVATION

Project Motivation

- From NYC open Data for NYPD arrests in 2024
- New York City is the most populous city in the US
  - Brooklyn, Queens, Manhattan, Bronx, Staten Island (order of population)
- Crime statistics can be used for law enforcement
- Crime has increased dramatically in recent years

Central Question

How can we leverage patterns and offense levels to better allocate resources and prevent crime?

Other Questions

How does incorporating demographic data affect the accuracy of our model?

Are some areas more susceptible to arrests than others?

What's the trend of the top offenses over the year?

NYPD Arrest Data 2024

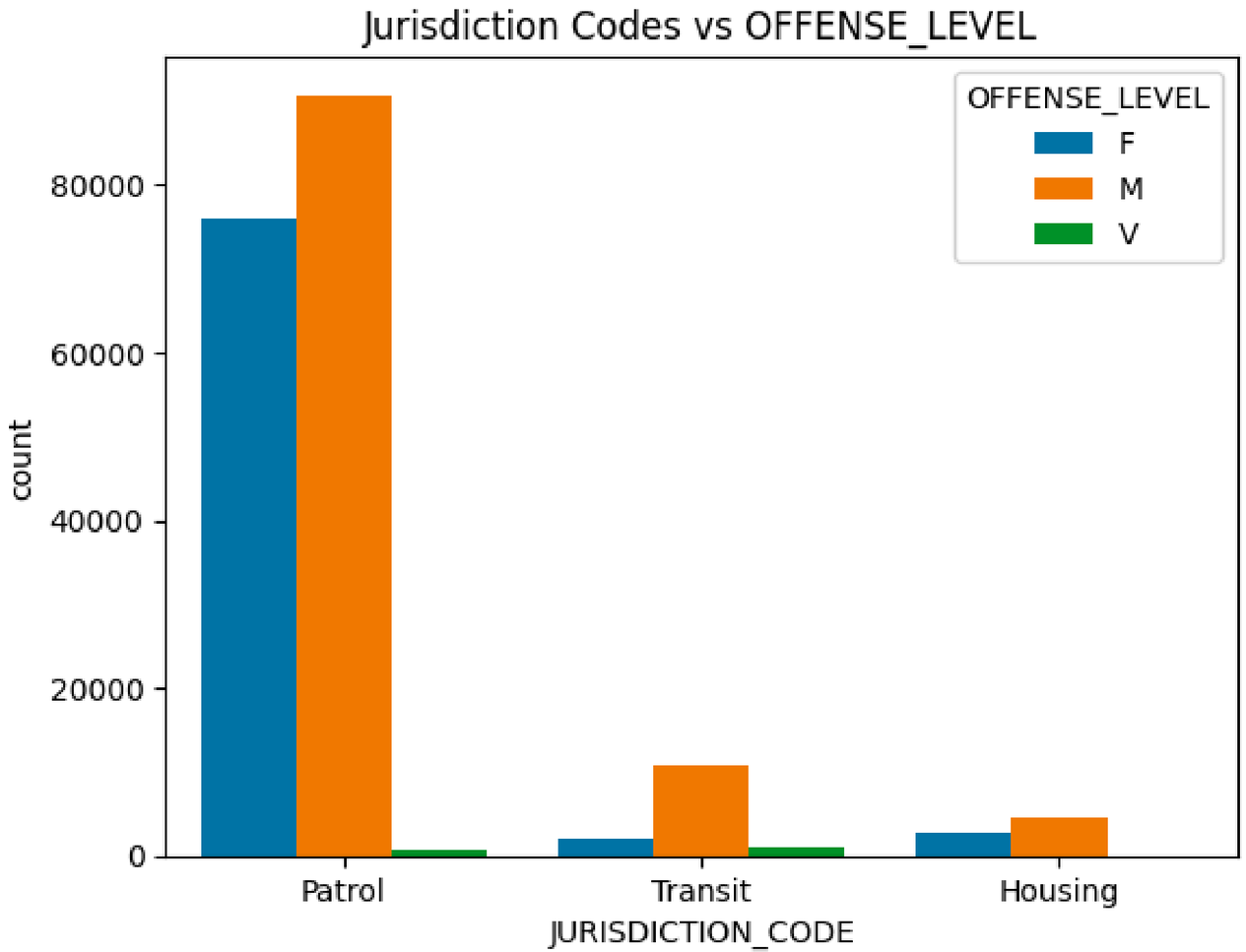
Felony	Misdemeanor	Violation
Highest Severity	Lower Severity	Lowest Severity (ex: traffic violation)

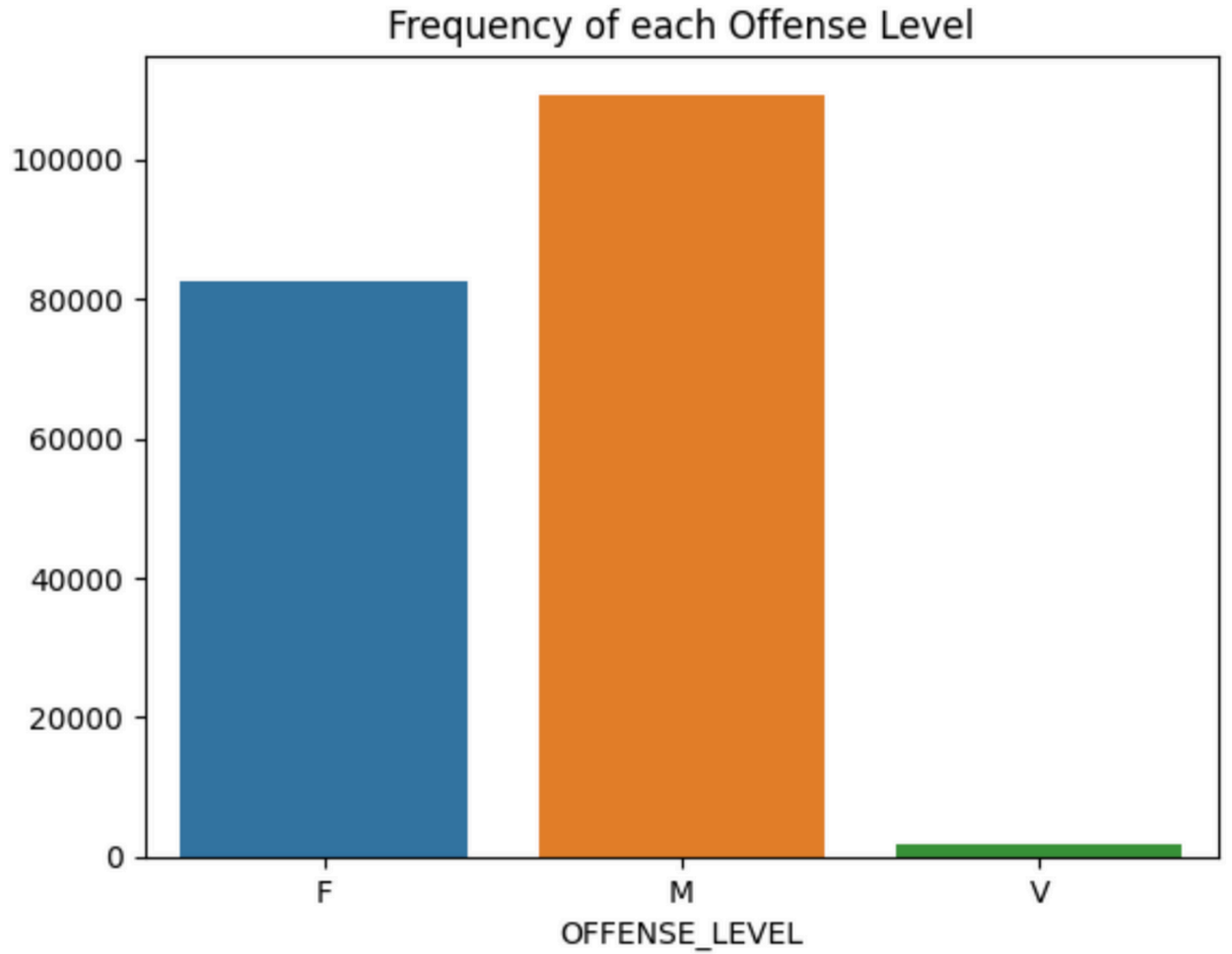
EXPLORATORY DATA ANALYSIS

The Data

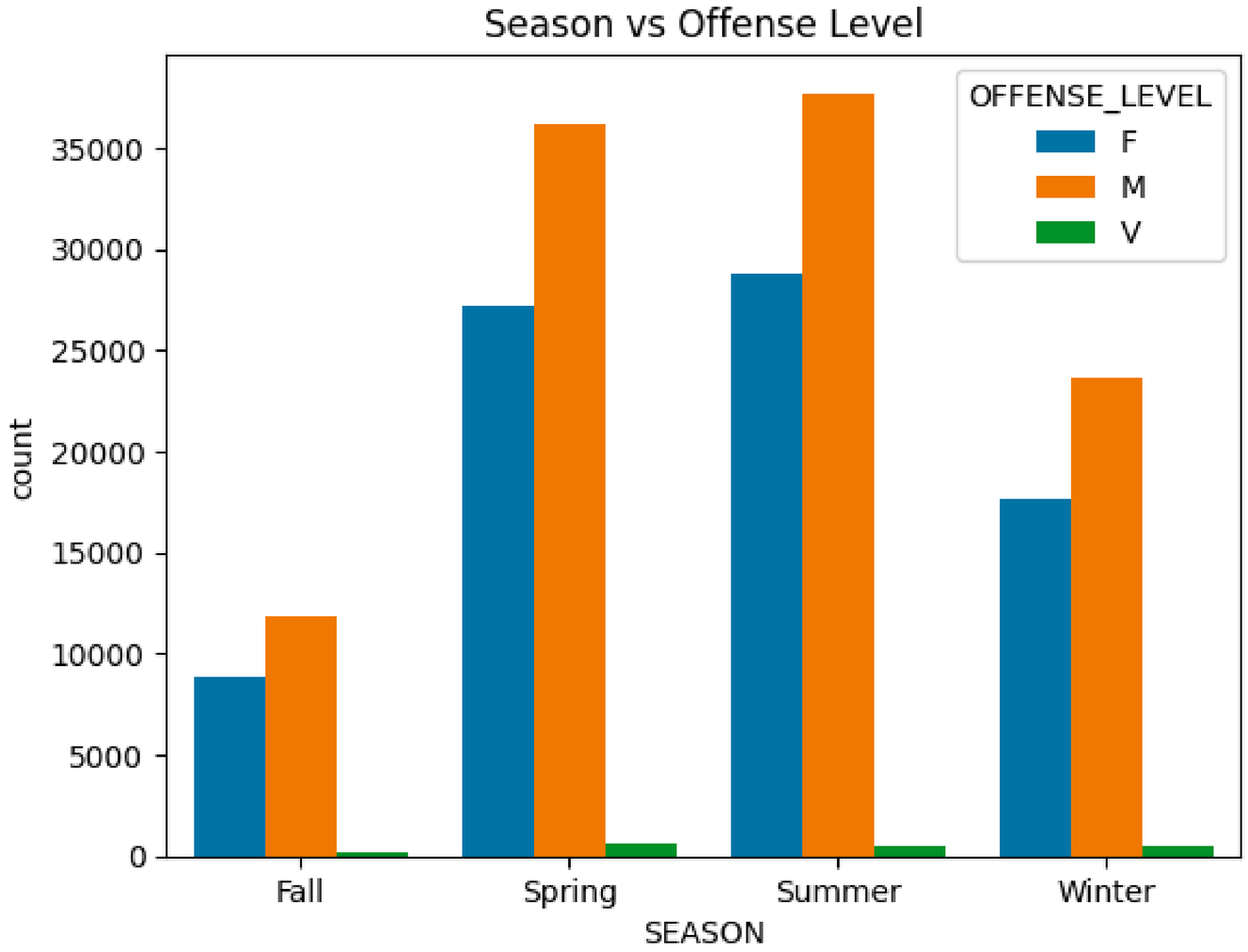
- Data from 2024, updated quarterly (from NYC Open Data)
- 195,447 rows × 19 columns --> 193,610 rows after cleaning
- Features like…
  - **ID’s, Arrest Date**
  - **PD_CD, KY_CD**: Codes for the offenses (KY more general)
  - **PD_DESC, OFNS_DESC**: Description of crime
  - **Precinct, Jurisdiction, Neighborhood, Latitude/Longitude**
  - **Demographics**
    - Age, Gender, Race
  - **Offense Level (What we’re predicting!!!)**

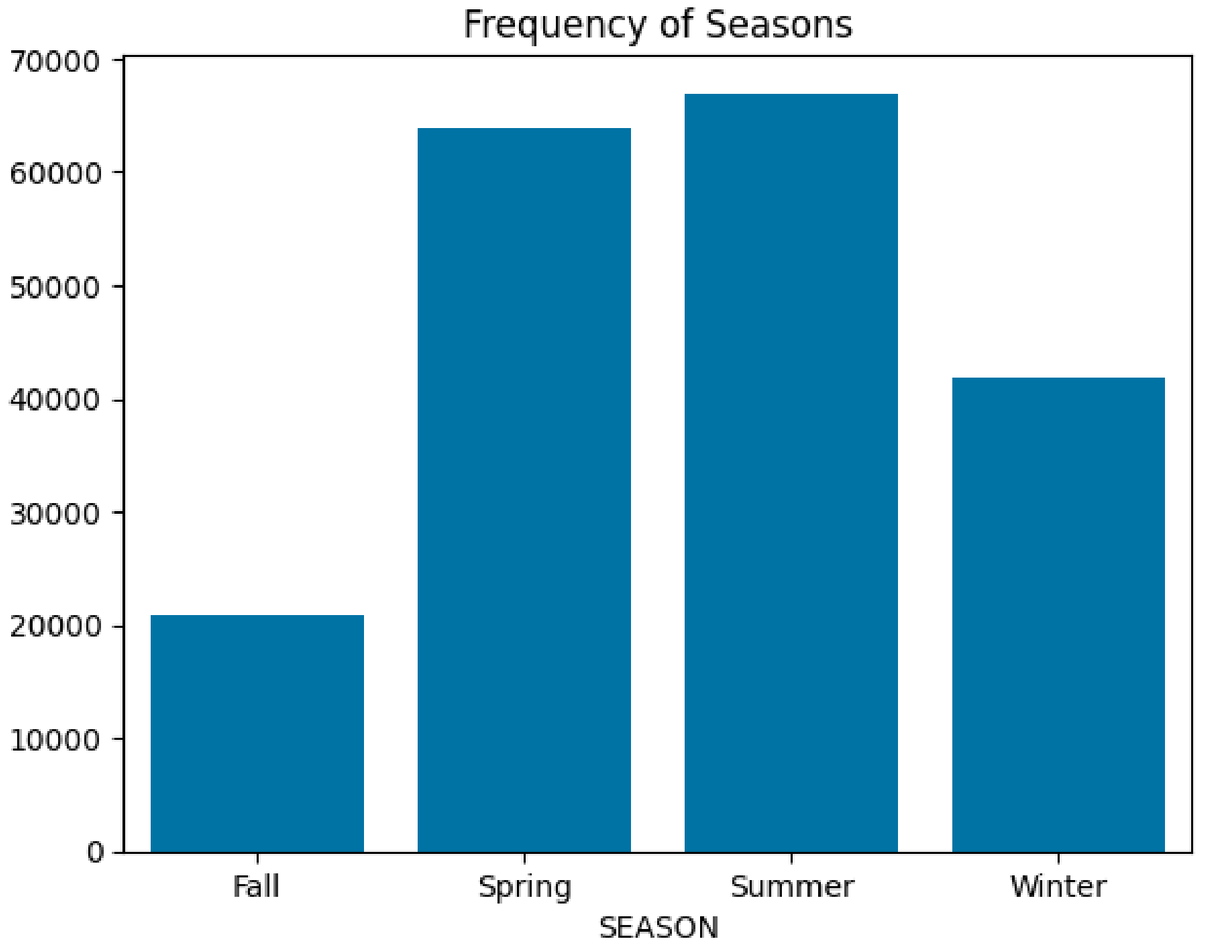
EDA


Jurisdiction Codes vs OFFENSE_LEVEL
OFFENSE_LEVEL
F
M
V
80000
60000
40000
20000
0
count
Patrol
Transit
Housing
JURISDICTION_CODE

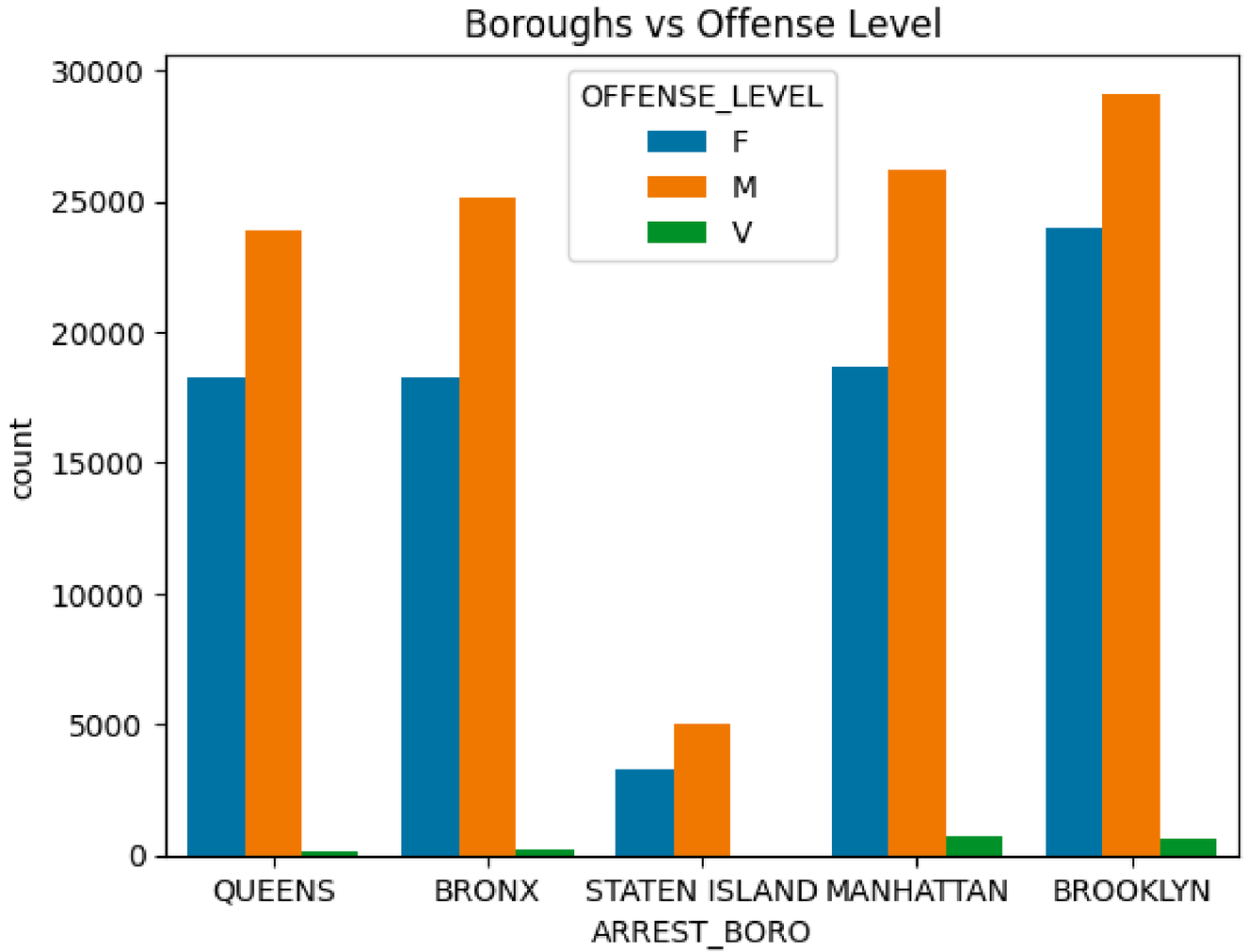

Frequency of each Offense Level
100000
80000
60000
40000
20000
0
F
M
V
OFFENSE_LEVEL

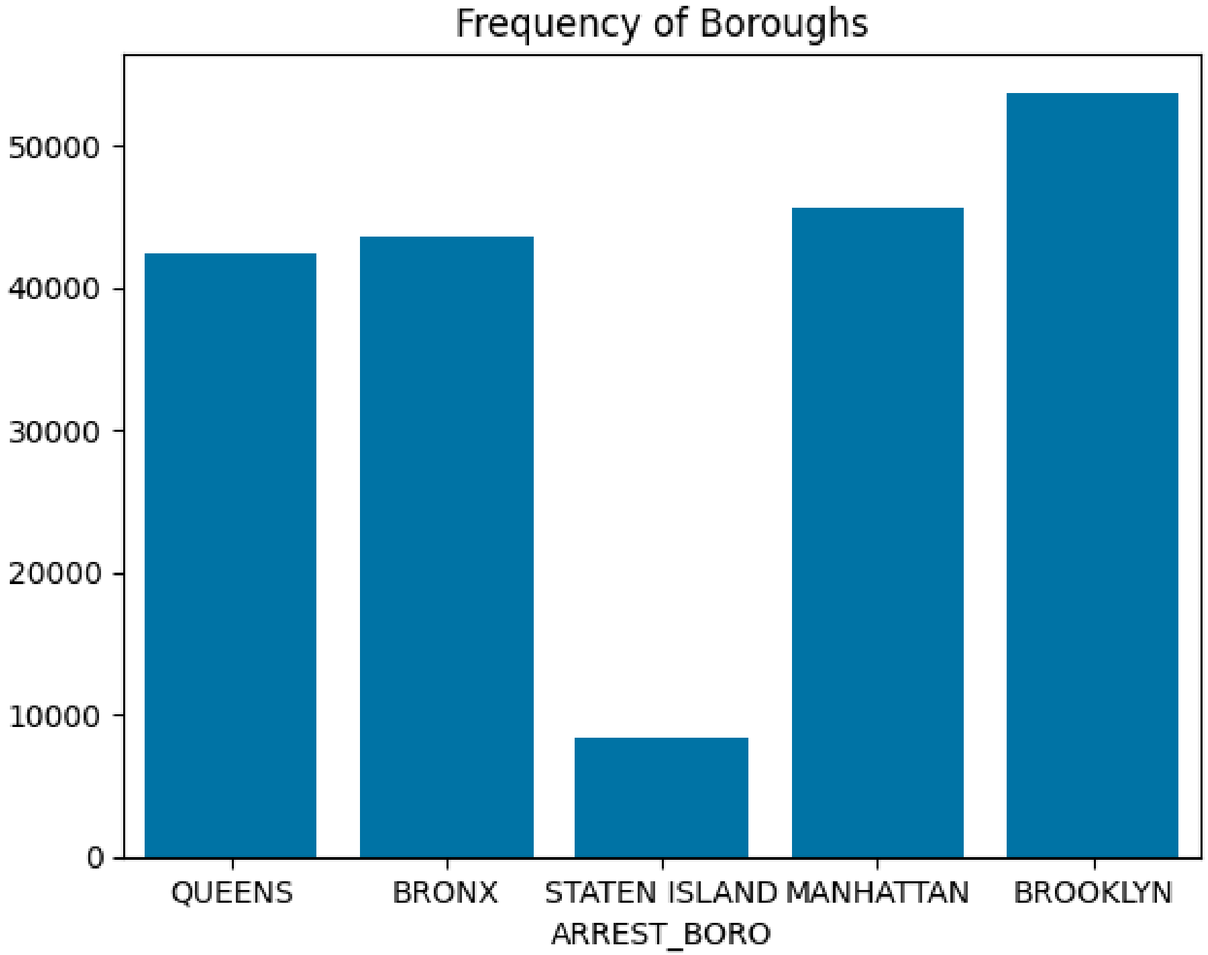
EDA


Season vs Offense Level
OFFENSE_LEVEL
F
M
V
count
35000
30000
25000
20000
15000
10000
5000
0
Fall
Spring
Summer
Winter
SEASON

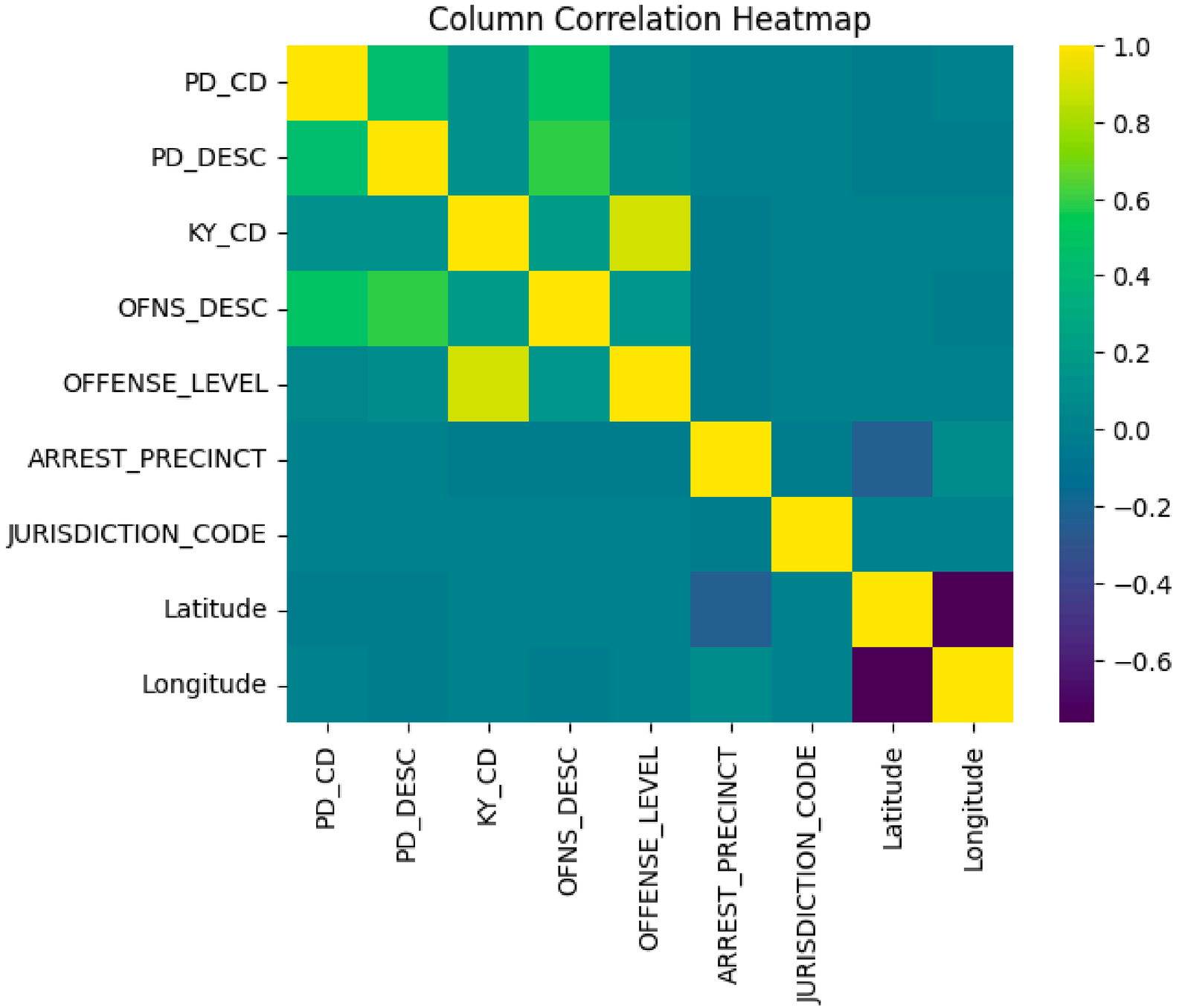

Frequency of Seasons
70000
60000
50000
40000
30000
20000
10000
0
Fall
Spring
Summer
Winter
SEASON

EDA

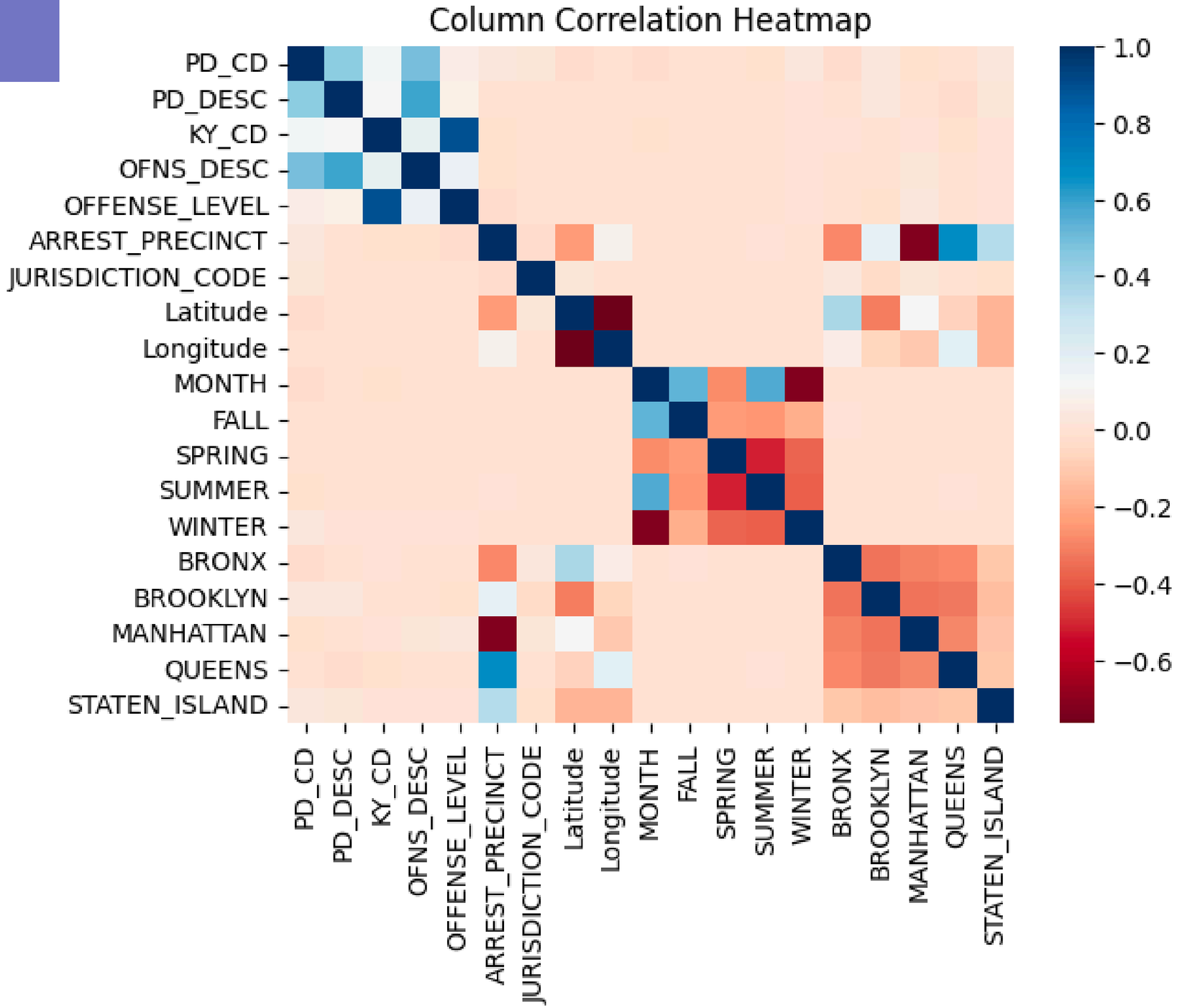

Boroughs vs Offense Level
OFFENSE_LEVEL
F
M
V
count
30000
25000
20000
15000
10000
5000
0
QUEENS
BRONX
STATEN ISLAND
MANHATTAN
BROOKLYN
ARREST_BORO


Frequency of Boroughs
50000
40000
30000
20000
10000
0
QUEENS
BRONX
STATEN ISLAND
MANHATTAN
BROOKLYN
ARREST_BORO

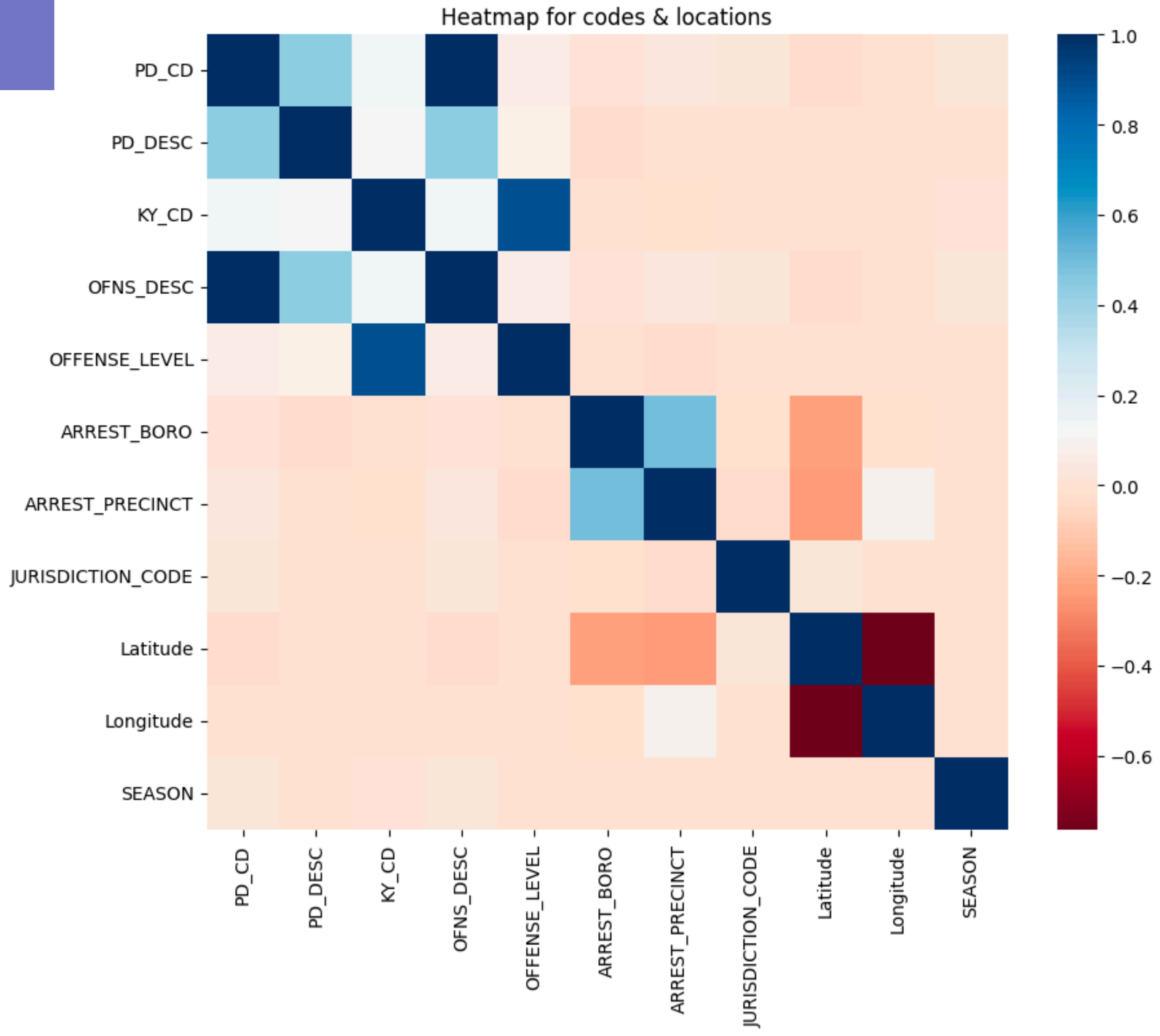
EDA


Column Correlation Heatmap
PD_CD
PD_DESC
KY_CD
OFNS_DESC
OFFENSE_LEVEL
ARREST_PRECINCT
JURISDICTION_CODE
Latitude
Longitude
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4
−0.6

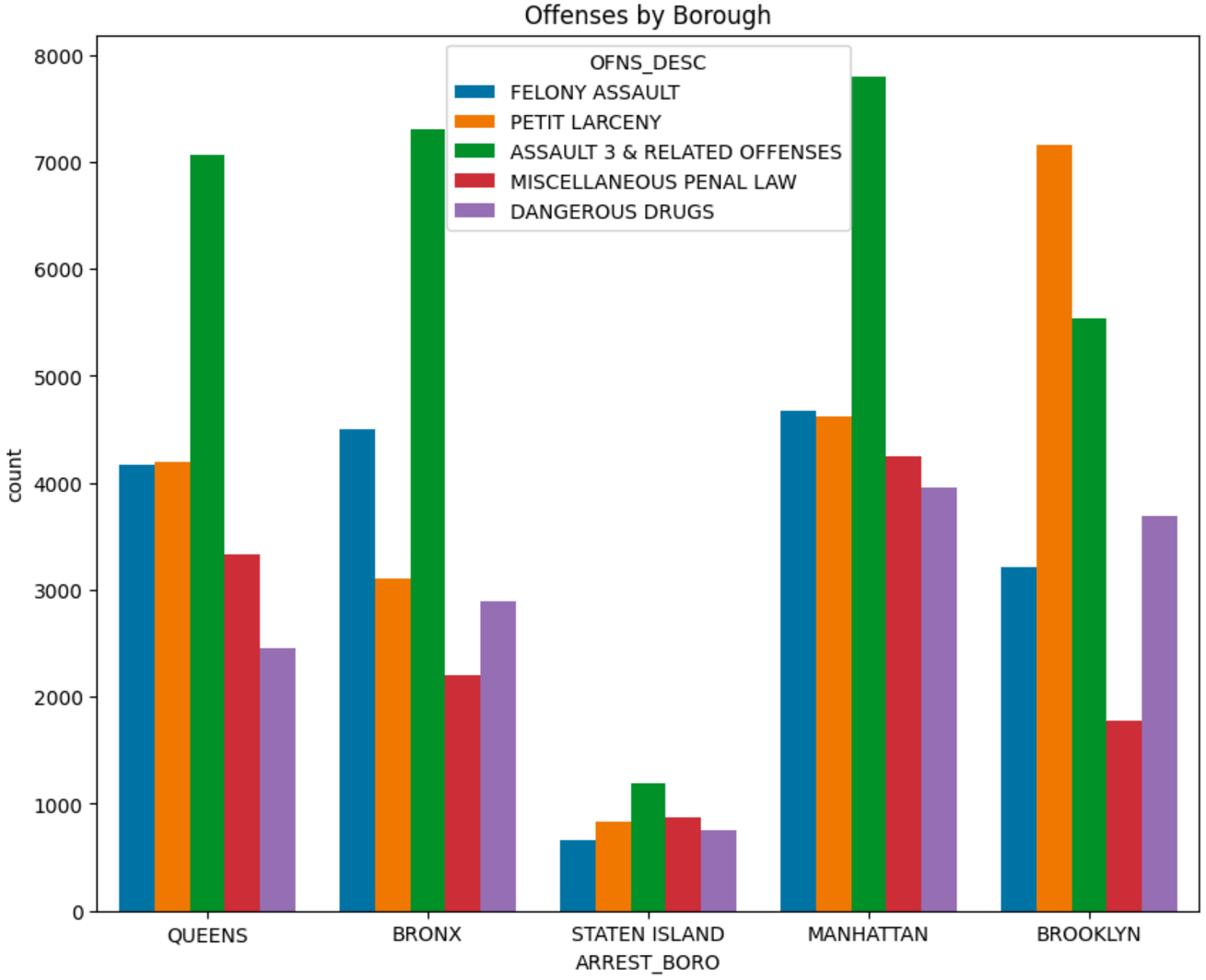
EDA

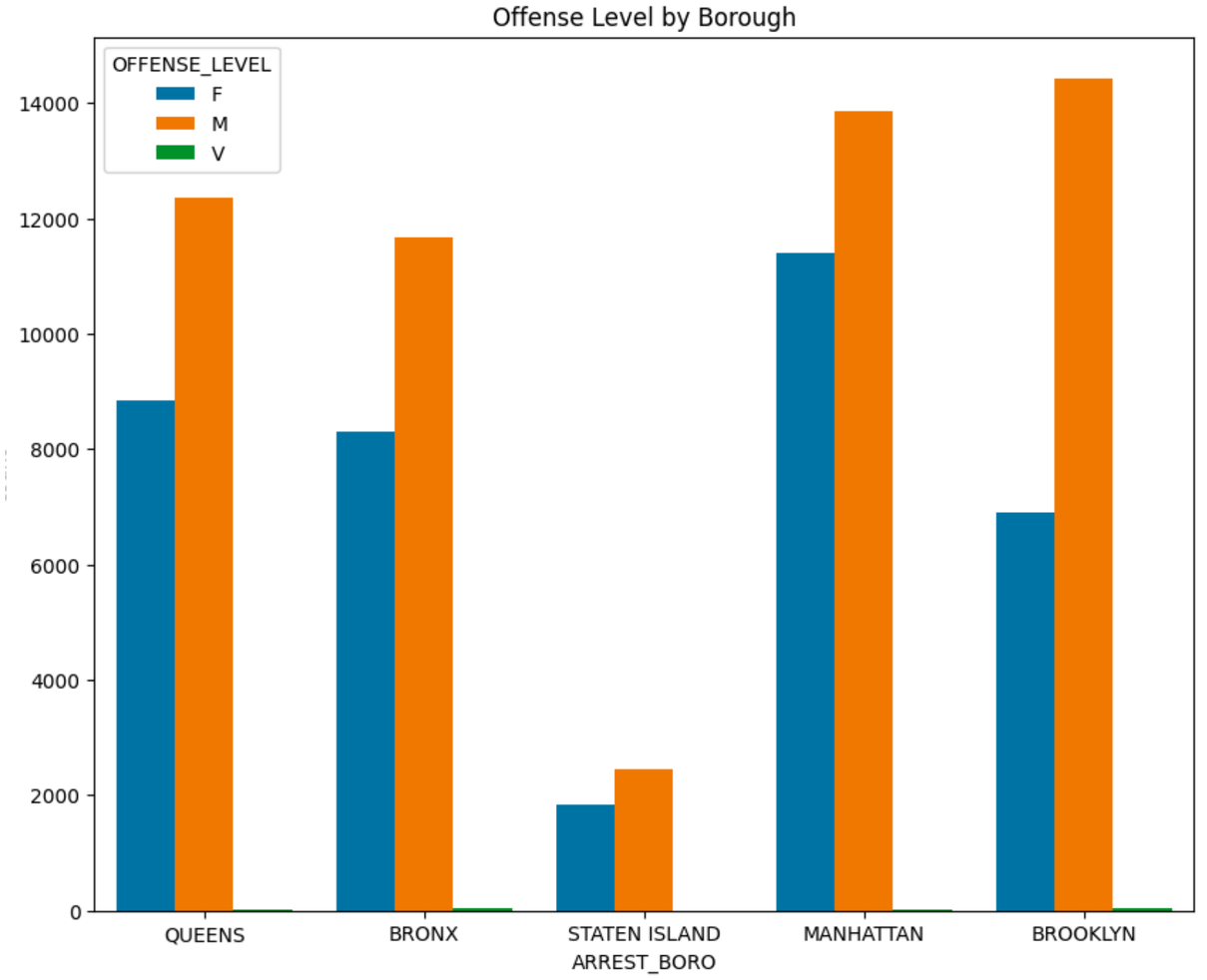

Column Correlation Heatmap
PD_CD
PD_DESC
KY_CD
OFNS_DESC
OFFENSE_LEVEL
ARREST_PRECINCT
JURISDICTION_CODE
Latitude
Longitude
MONTH
FALL
SPRING
SUMMER
WINTER
BRONX
BROOKLYN
MANHATTAN
QUEENS
STATEN_ISLAND
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4
−0.6

EDA

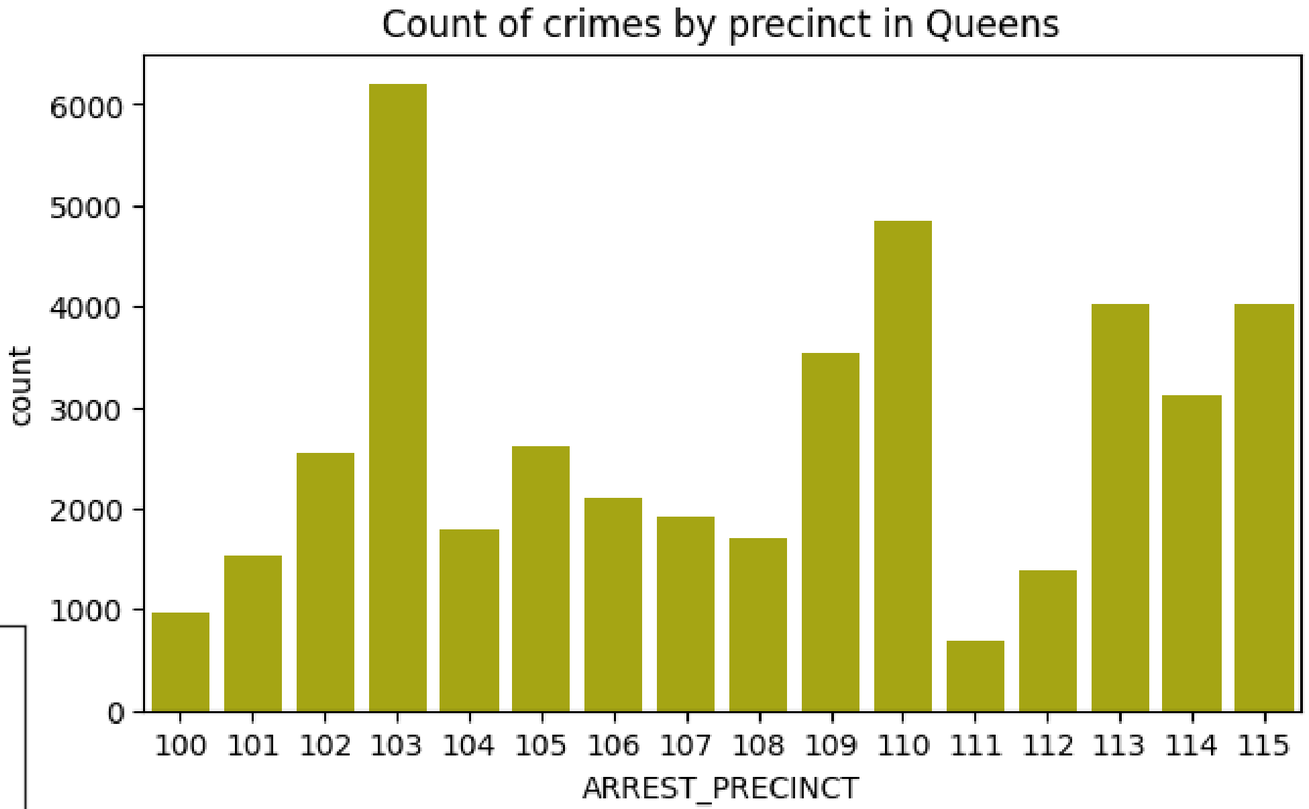

Heatmap for codes & locations
PD_CD
PD_DESC
KY_CD
OFNS_DESC
OFFENSE_LEVEL
ARREST_BORO
ARREST_PRECINCT
JURISDICTION_CODE
Latitude
Longitude
SEASON
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4
−0.6

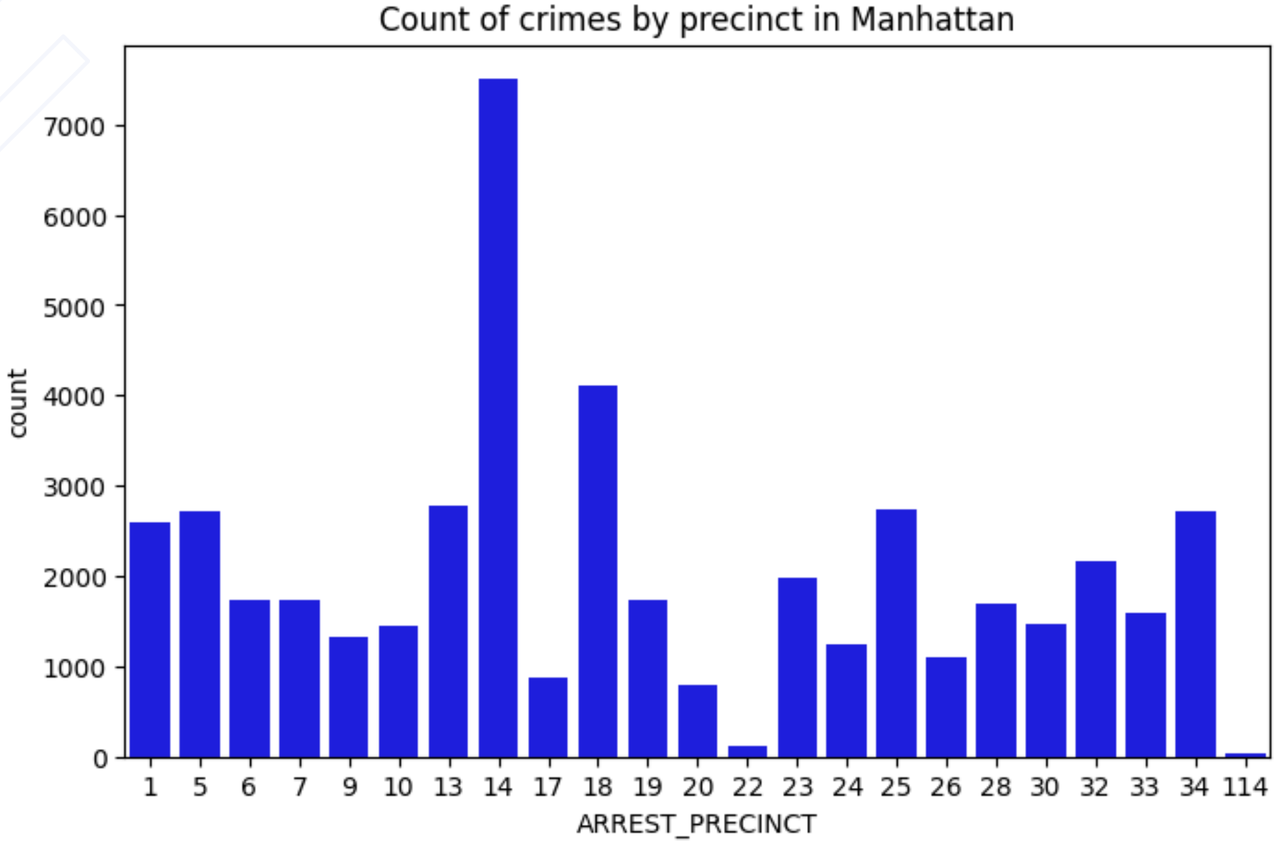
EDA


Offenses by Borough
OFNS_DESC
FELONY ASSAULT
PETIT LARCENY
ASSAULT 3 & RELATED OFFENSES
MISCELLANEOUS PENAL LAW
DANGEROUS DRUGS
count
0
1000
2000
3000
4000
5000
6000
7000
8000
QUEENS
BRONX
STATEN ISLAND
MANHATTAN
BROOKLYN
ARREST_BORO

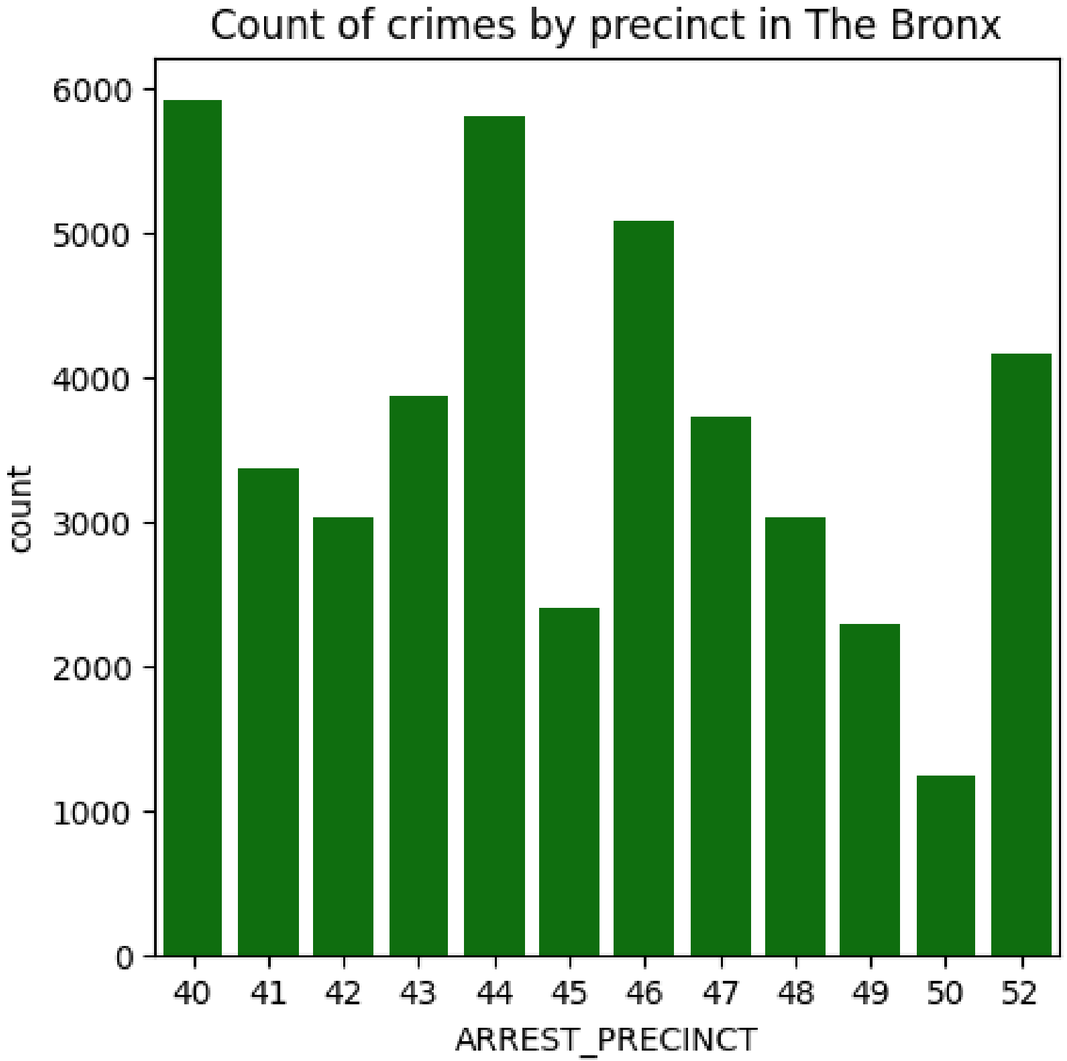

Offense Level by Borough
OFFENSE_LEVEL
F
M
V
0
2000
4000
6000
8000
10000
12000
14000
QUEENS
BRONX
STATEN ISLAND
MANHATTAN
BROOKLYN
ARREST_BORO

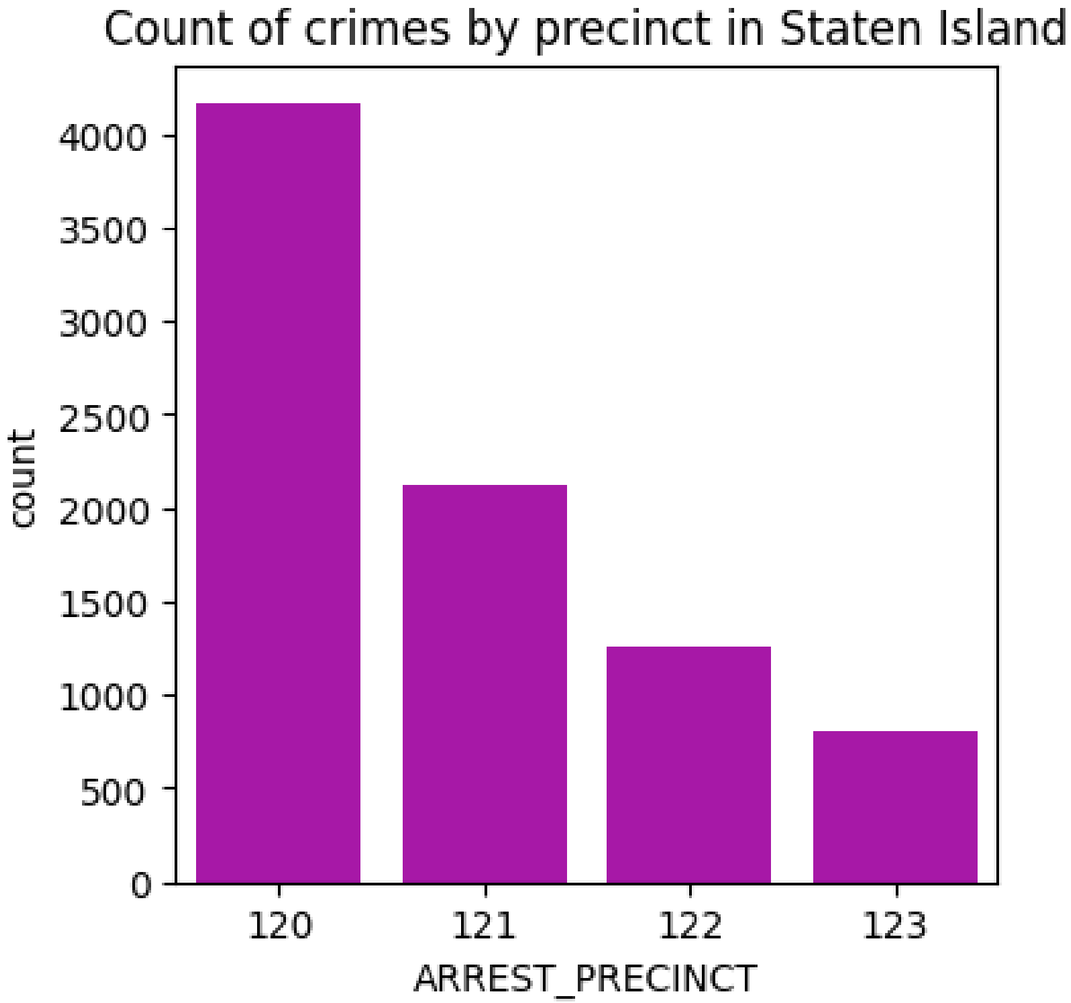
EDA


Count of crimes by precinct in Queens
count
0
1000
2000
3000
4000
5000
6000
100 101 102 103 104 105 106 107 108 109 110 111 112 113 114 115
ARREST_PRECINCT

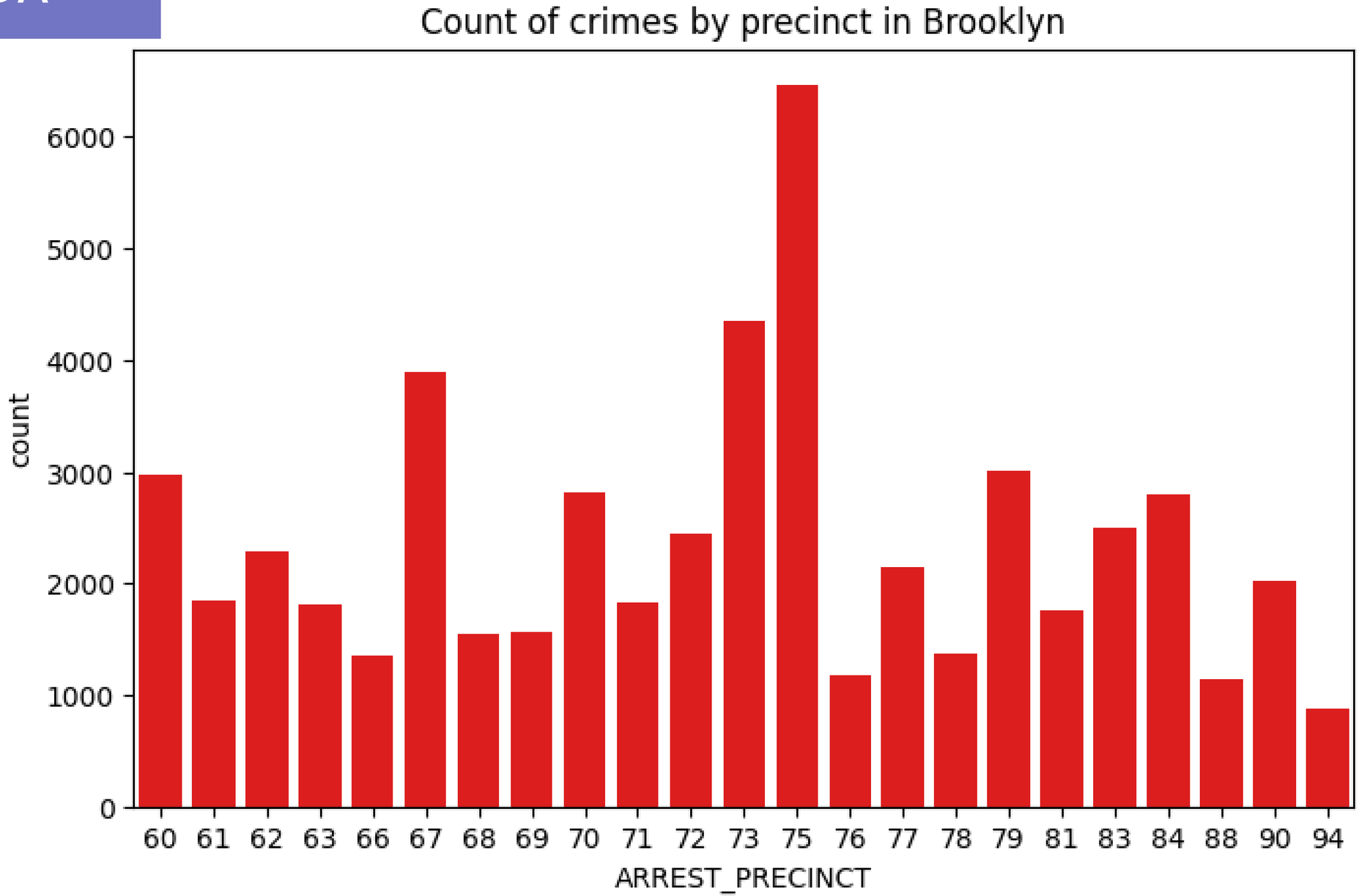

Count of crimes by precinct in Manhattan
count
0
1000
2000
3000
4000
5000
6000
7000
1 5 6 7 9 10 13 14 17 18 19 20 22 23 24 25 26 28 30 32 33 34 114
ARREST_PRECINCT

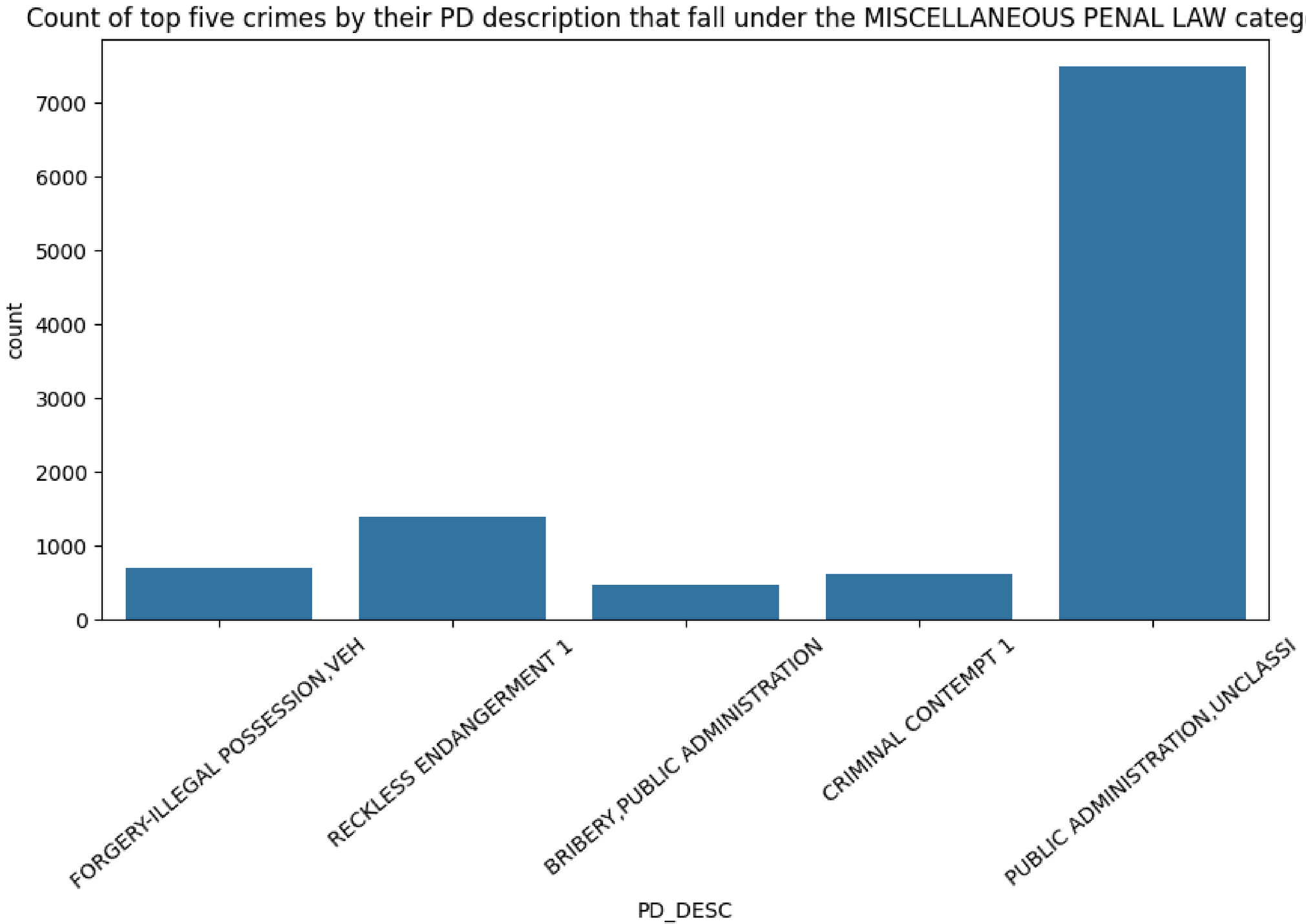
EDA


Count of crimes by precinct in The Bronx
count
6000
5000
4000
3000
2000
1000
0
40
41
42
43
44
45
46
47
48
49
50
52
ARREST_PRECINCT

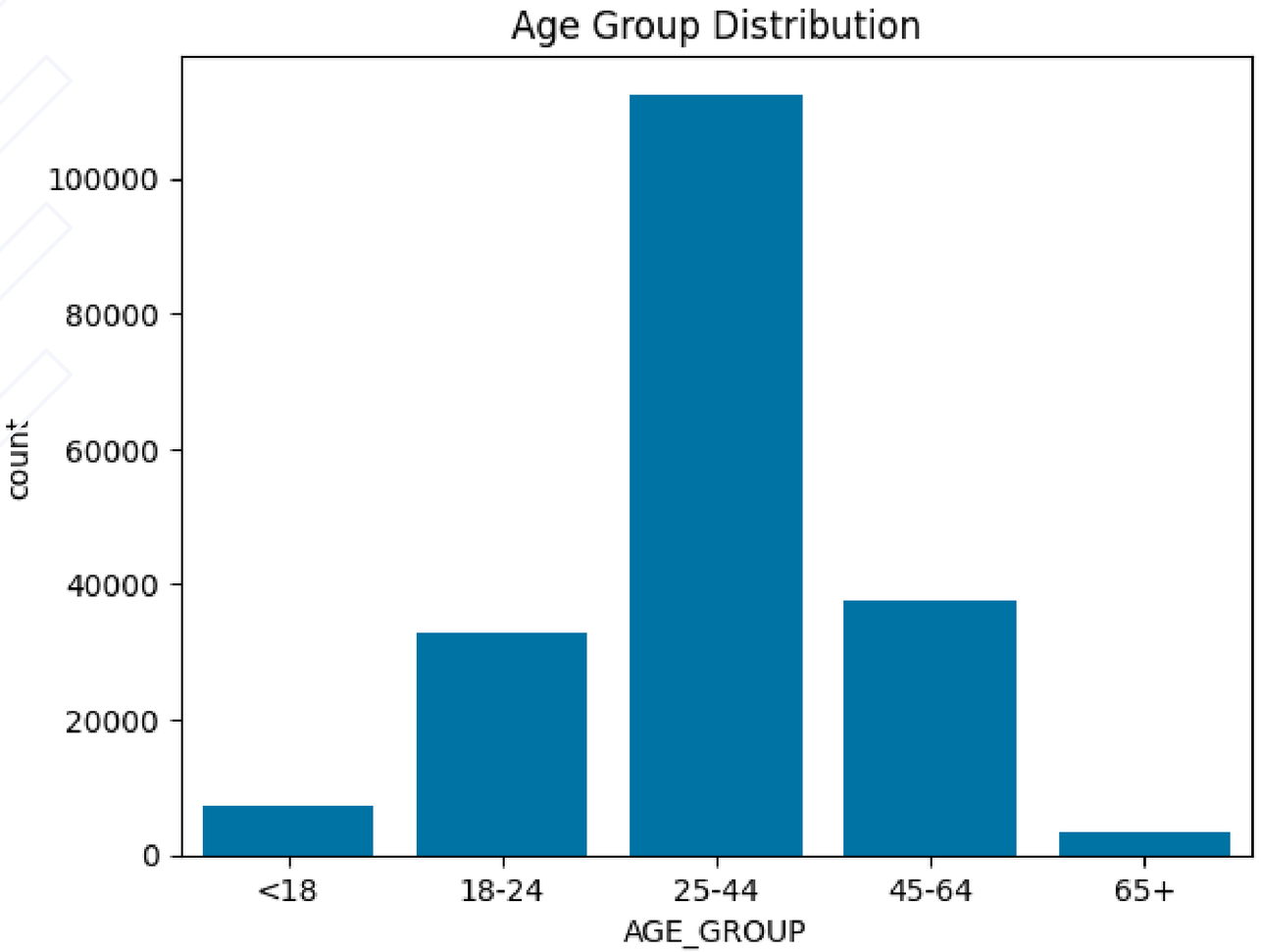

Count of crimes by precinct in Staten Island
count
4000
3500
3000
2500
2000
1500
1000
500
0
120
121
122
123
ARREST_PRECINCT

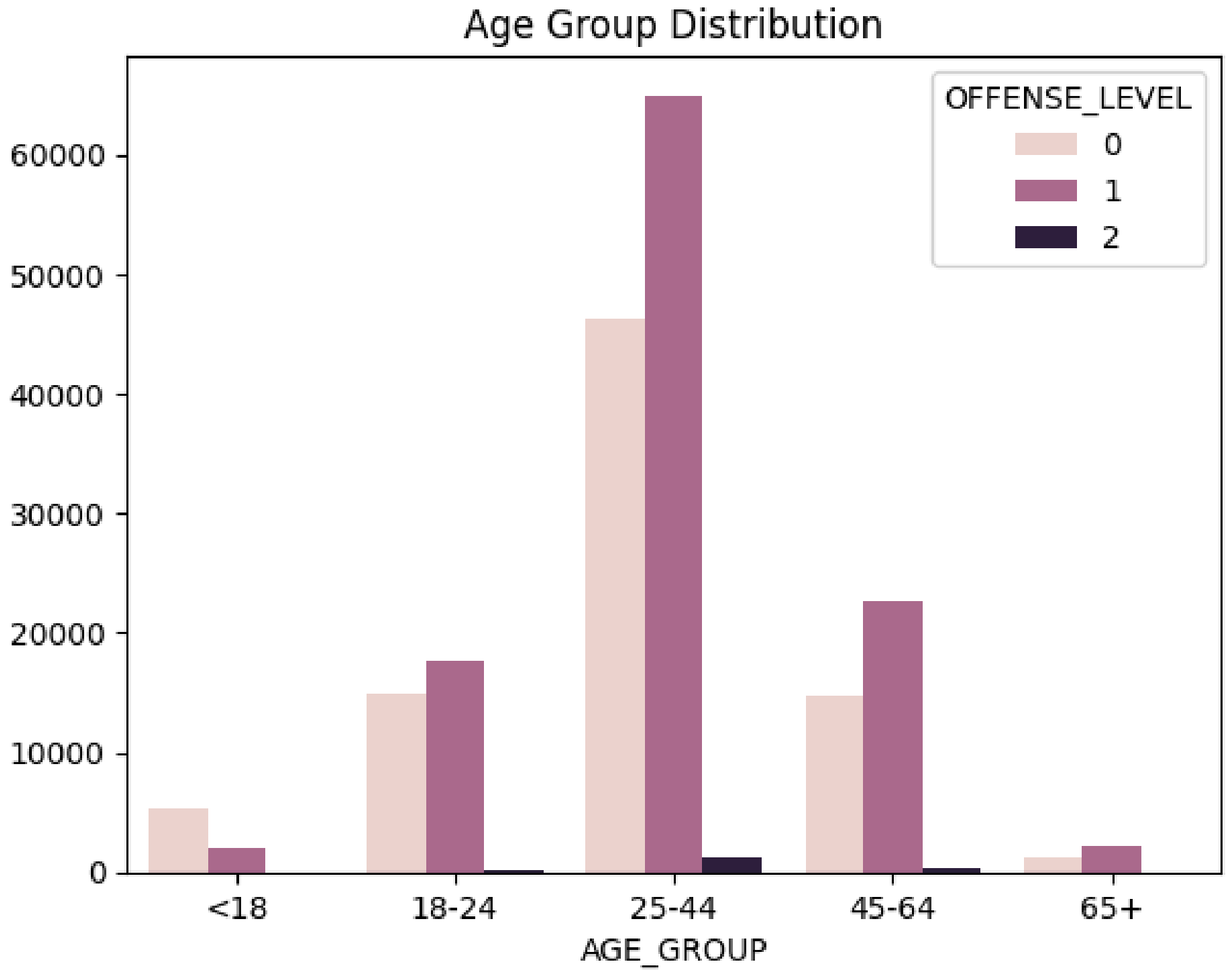
EDA


Count of crimes by precinct in Brooklyn
count
0
1000
2000
3000
4000
5000
6000
60
61
62
63
66
67
68
69
70
71
72
73
75
76
77
78
79
81
83
84
88
90
94
ARREST_PRECINCT

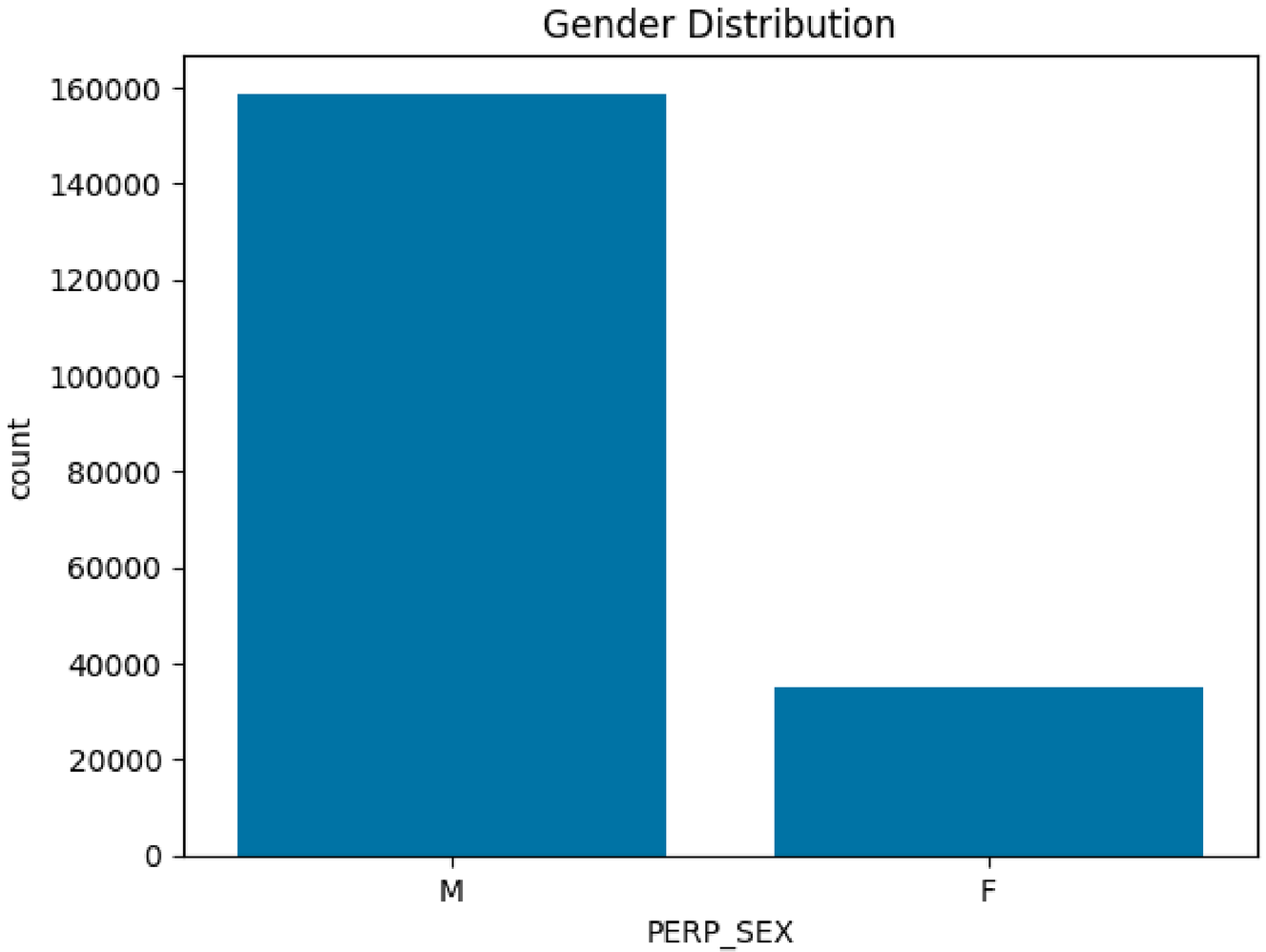

Count of top five crimes by their PD description that fall under the MISCELLANEOUS PENAL LAW category
count
7000
6000
5000
4000
3000
2000
1000
0
FORGERY-ILLEGAL POSSESSION,VEH
RECKLESS ENDANGERMENT 1
BRIBERY,PUBLIC ADMINISTRATION
CRIMINAL CONTEMPT 1
PUBLIC ADMINISTRATION,UNCLASSI
PD_DESC

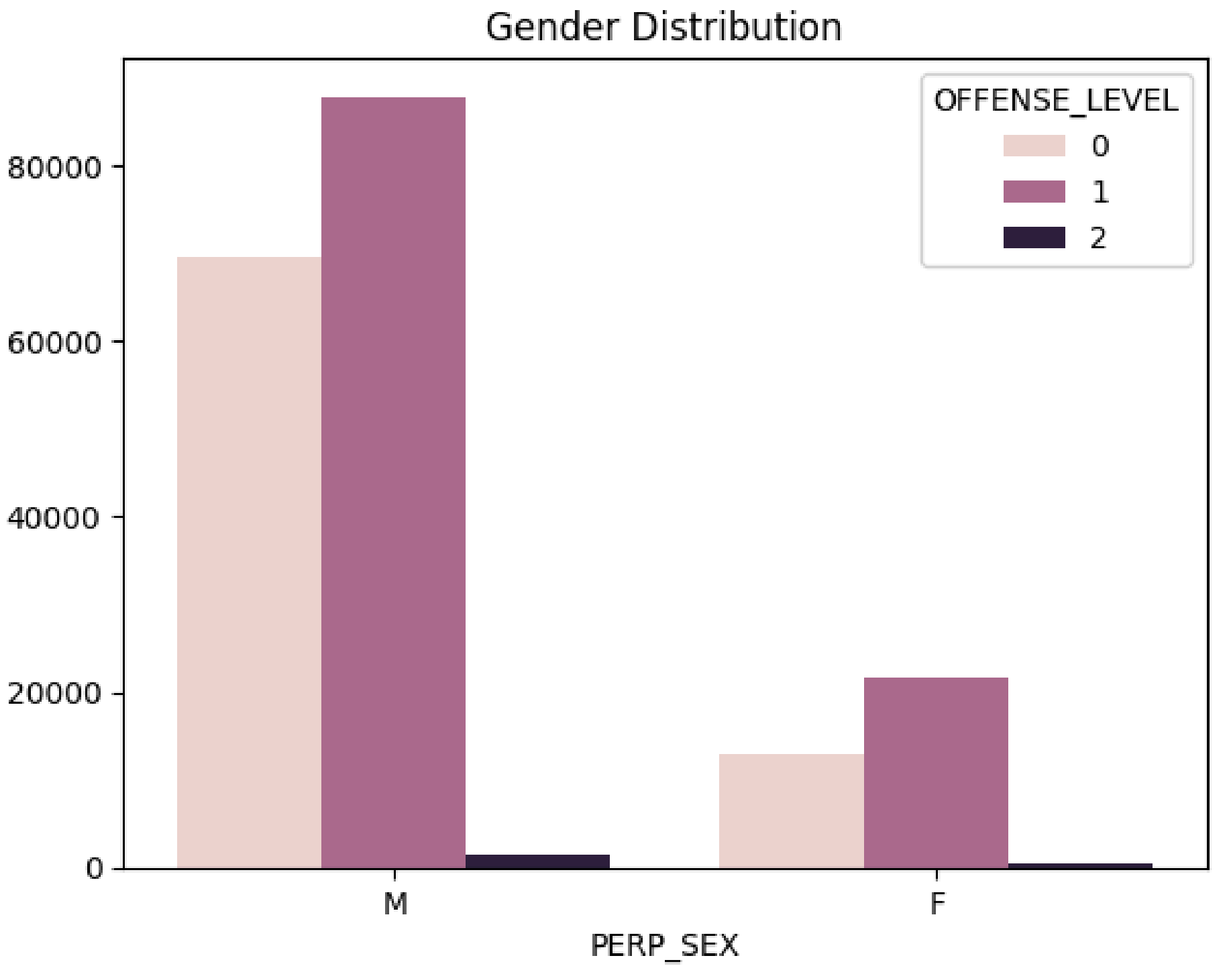
EDA


Age Group Distribution
count
100000
80000
60000
40000
20000
0
<18
18-24
25-44
45-64
65+
AGE_GROUP

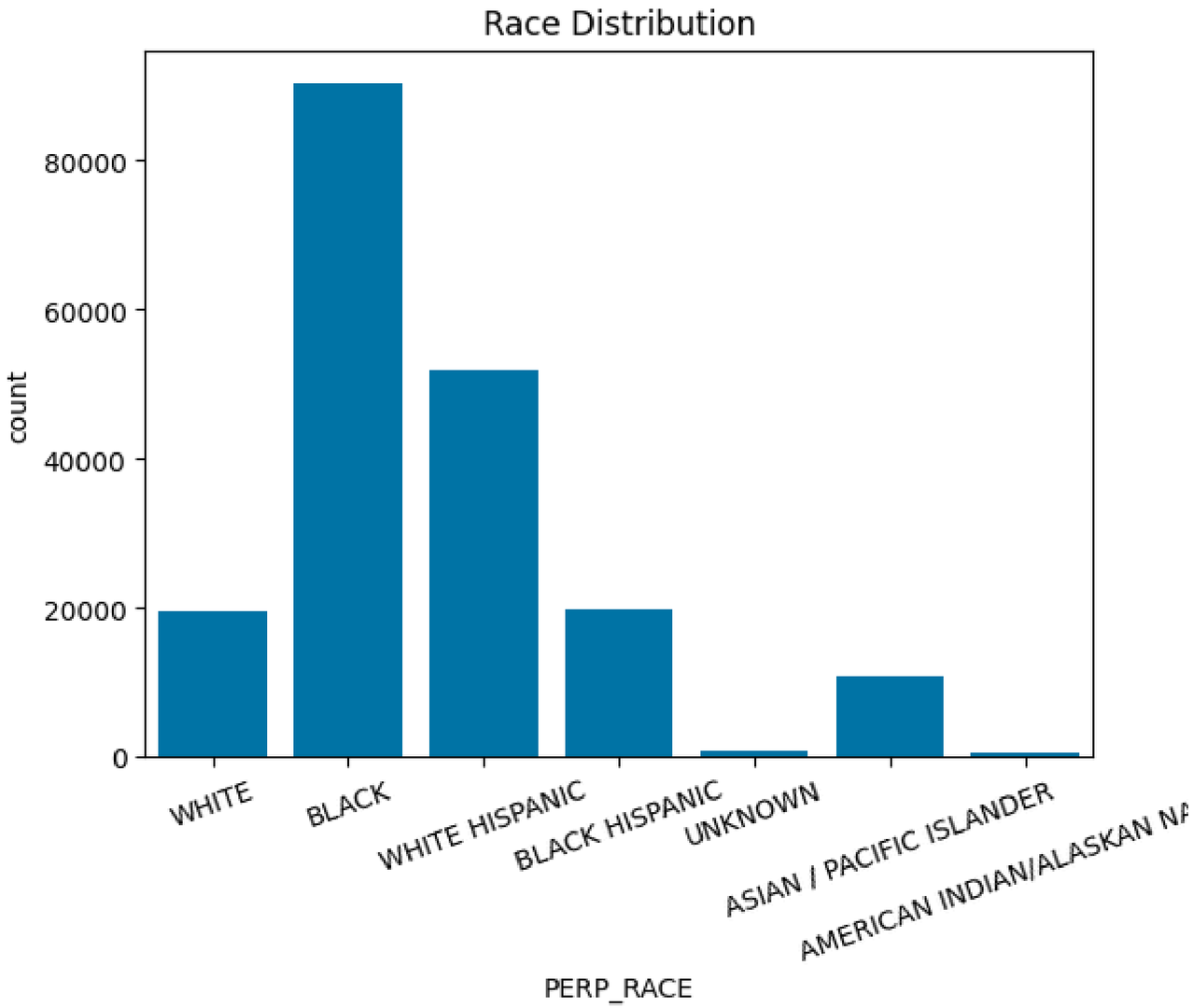

Age Group Distribution
OFFENSE_LEVEL
0
1
2
60000
50000
40000
30000
20000
10000
0
<18
18-24
25-44
45-64
65+
AGE_GROUP

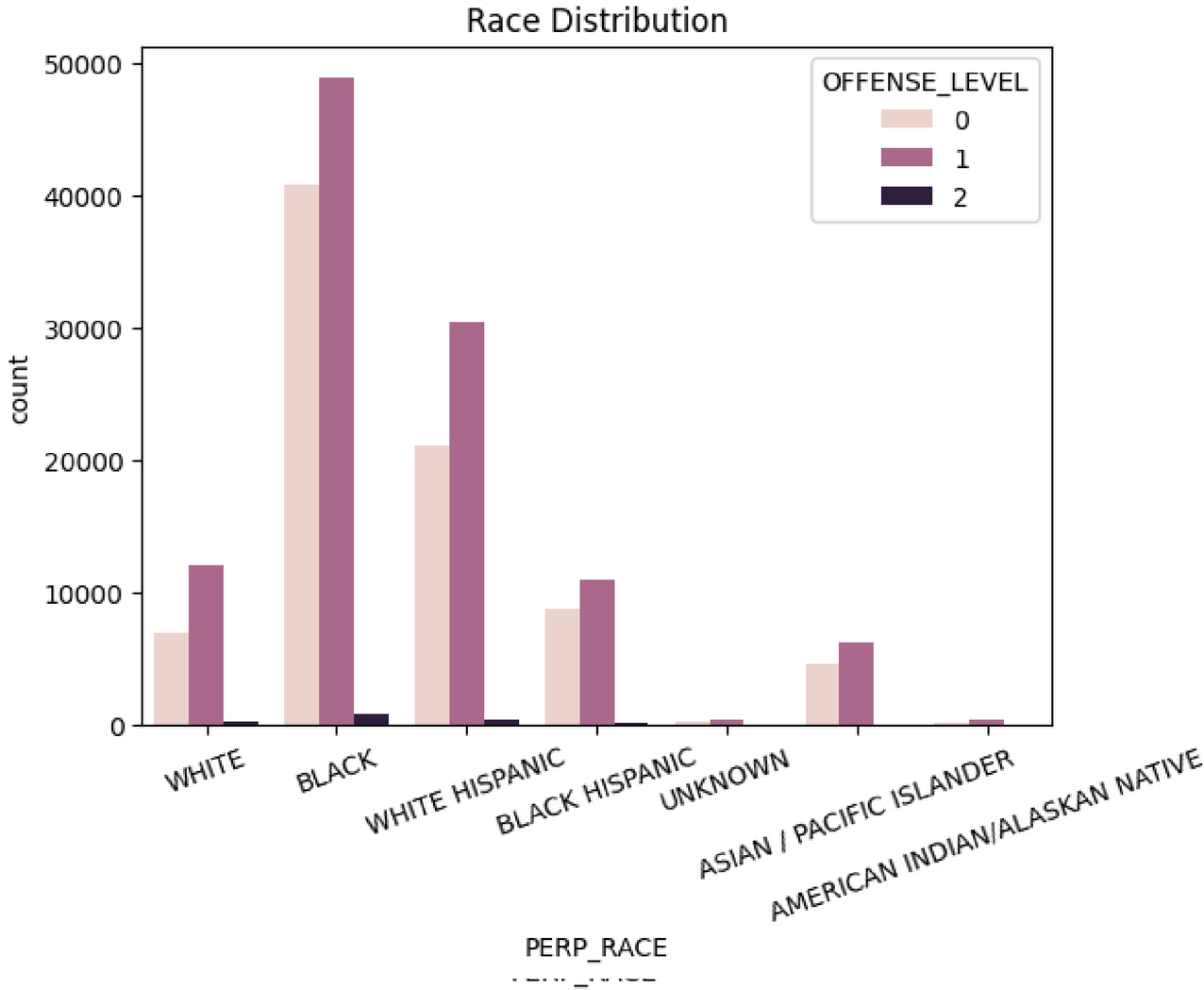
EDA


Gender Distribution
160000
140000
120000
100000
80000
60000
40000
20000
0
count
M
F
PERP_SEX

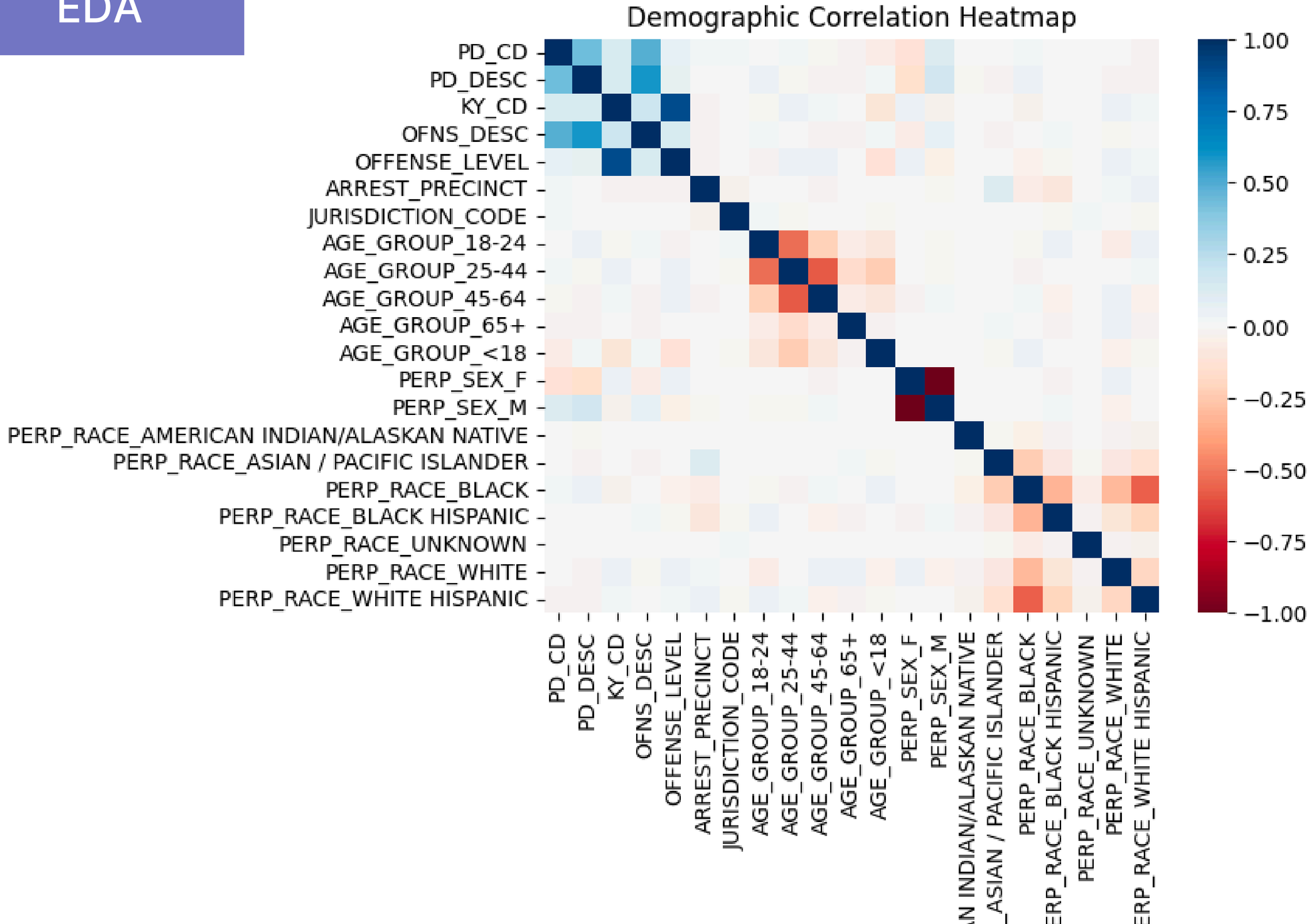

Gender Distribution
OFFENSE_LEVEL
0
1
2
80000
60000
40000
20000
0
M
F
PERP_SEX

EDA

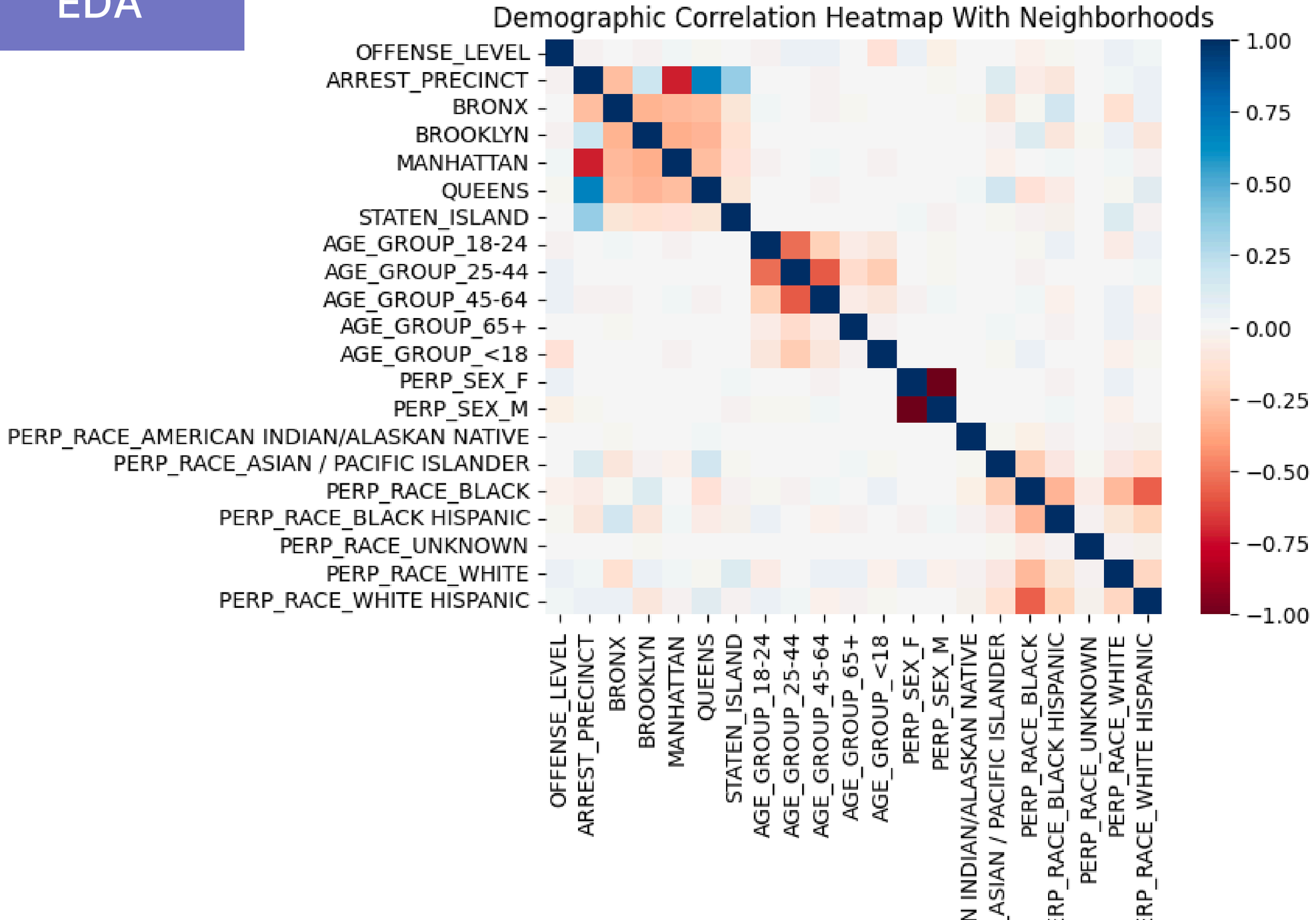

Race Distribution
count
80000
60000
40000
20000
0
WHITE
BLACK
WHITE HISPANIC
BLACK HISPANIC
UNKNOWN
ASIAN / PACIFIC ISLANDER
AMERICAN INDIAN/ALASKAN NA
PERP_RACE


Race Distribution
OFFENSE_LEVEL
0
1
2
count
50000
40000
30000
20000
10000
0
WHITE
BLACK
WHITE HISPANIC
BLACK HISPANIC
UNKNOWN
ASIAN / PACIFIC ISLANDER
AMERICAN INDIAN/ALASKAN NATIVE
PERP_RACE

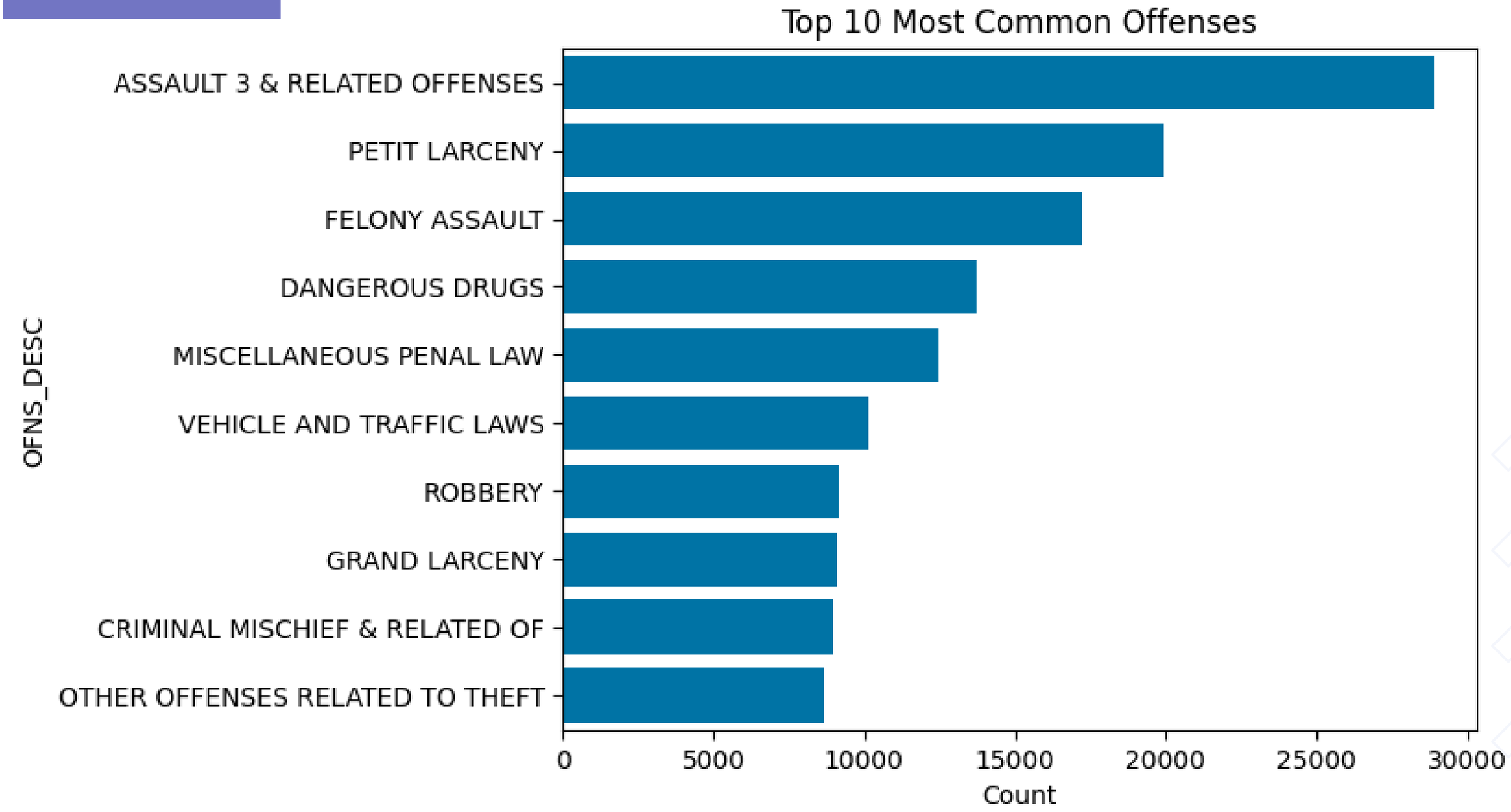
EDA


Demographic Correlation Heatmap
PD_CD
PD_DESC
KY_CD
OFNS_DESC
OFFENSE_LEVEL
ARREST_PRECINCT
JURISDICTION_CODE
AGE_GROUP_18-24
AGE_GROUP_25-44
AGE_GROUP_45-64
AGE_GROUP_65+
AGE_GROUP_<18
PERP_SEX_F
PERP_SEX_M
PERP_RACE_AMERICAN INDIAN/ALASKAN NATIVE
PERP_RACE_ASIAN / PACIFIC ISLANDER
PERP_RACE_BLACK
PERP_RACE_BLACK HISPANIC
PERP_RACE_UNKNOWN
PERP_RACE_WHITE
PERP_RACE_WHITE HISPANIC
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00

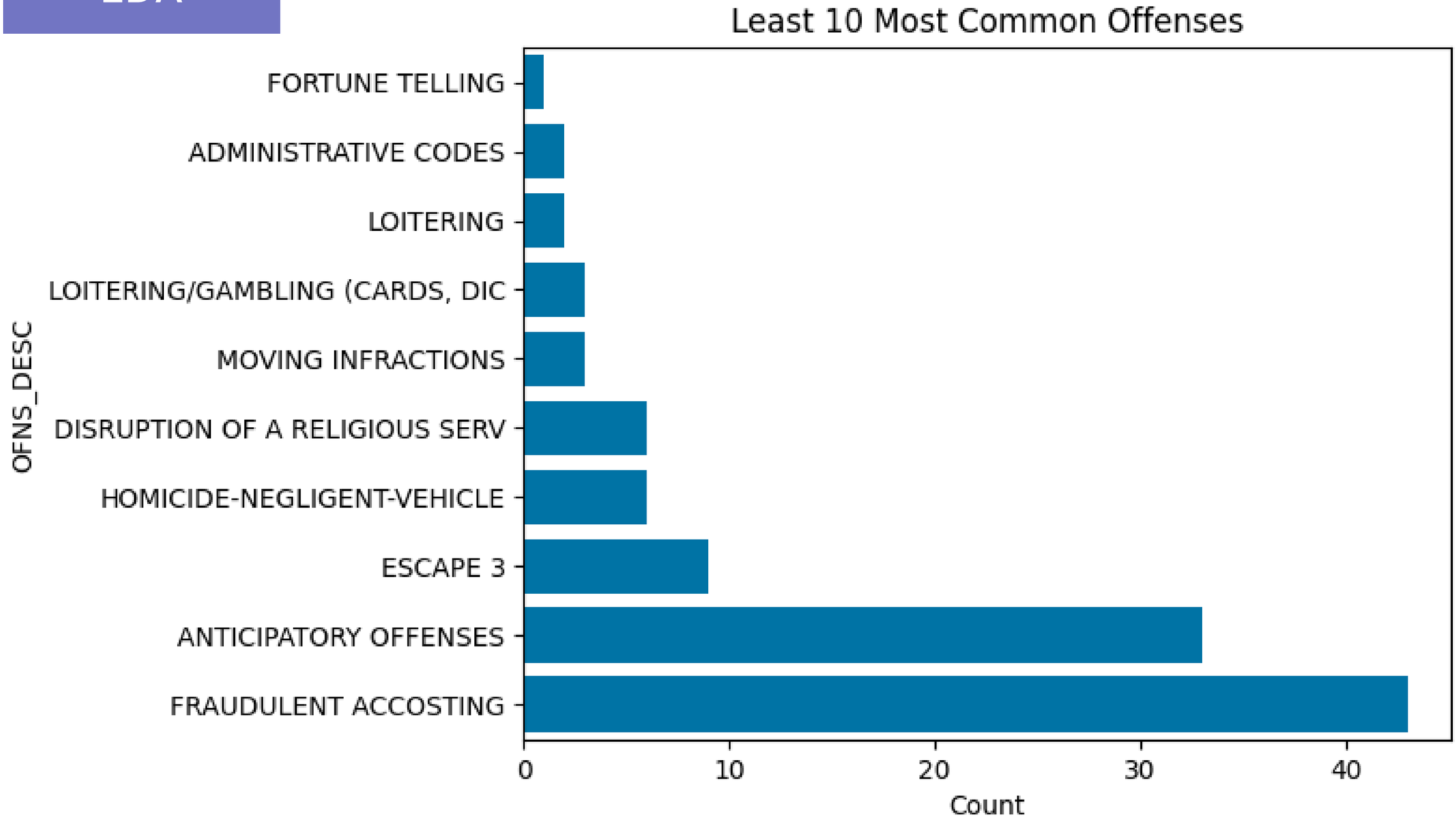
EDA


Demographic Correlation Heatmap With Neighborhoods
OFFENSE_LEVEL
ARREST_PRECINCT
BRONX
BROOKLYN
MANHATTAN
QUEENS
STATEN_ISLAND
AGE_GROUP_18-24
AGE_GROUP_25-44
AGE_GROUP_45-64
AGE_GROUP_65+
AGE_GROUP_<18
PERP_SEX_F
PERP_SEX_M
PERP_RACE_AMERICAN INDIAN/ALASKAN NATIVE
PERP_RACE_ASIAN / PACIFIC ISLANDER
PERP_RACE_BLACK
PERP_RACE_BLACK HISPANIC
PERP_RACE_UNKNOWN
PERP_RACE_WHITE
PERP_RACE_WHITE HISPANIC
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00

EDA


Top 10 Most Common Offenses
ASSAULT 3 & RELATED OFFENSES
PETIT LARCENY
FELONY ASSAULT
DANGEROUS DRUGS
MISCELLANEOUS PENAL LAW
VEHICLE AND TRAFFIC LAWS
ROBBERY
GRAND LARCENY
CRIMINAL MISCHIEF & RELATED OF
OTHER OFFENSES RELATED TO THEFT
OFNS_DESC
0
5000
10000
15000
20000
25000
30000
Count

EDA


Least 10 Most Common Offenses
FORTUNE TELLING
ADMINISTRATIVE CODES
LOITERING
LOITERING/GAMBLING (CARDS, DIC
MOVING INFRACTIONS
DISRUPTION OF A RELIGIOUS SERV
HOMICIDE-NEGLIGENT-VEHICLE
ESCAPE 3
ANTICIPATORY OFFENSES
FRAUDULENT ACCOSTING
OFNS_DESC
0
10
20
30
40
Count

EDA

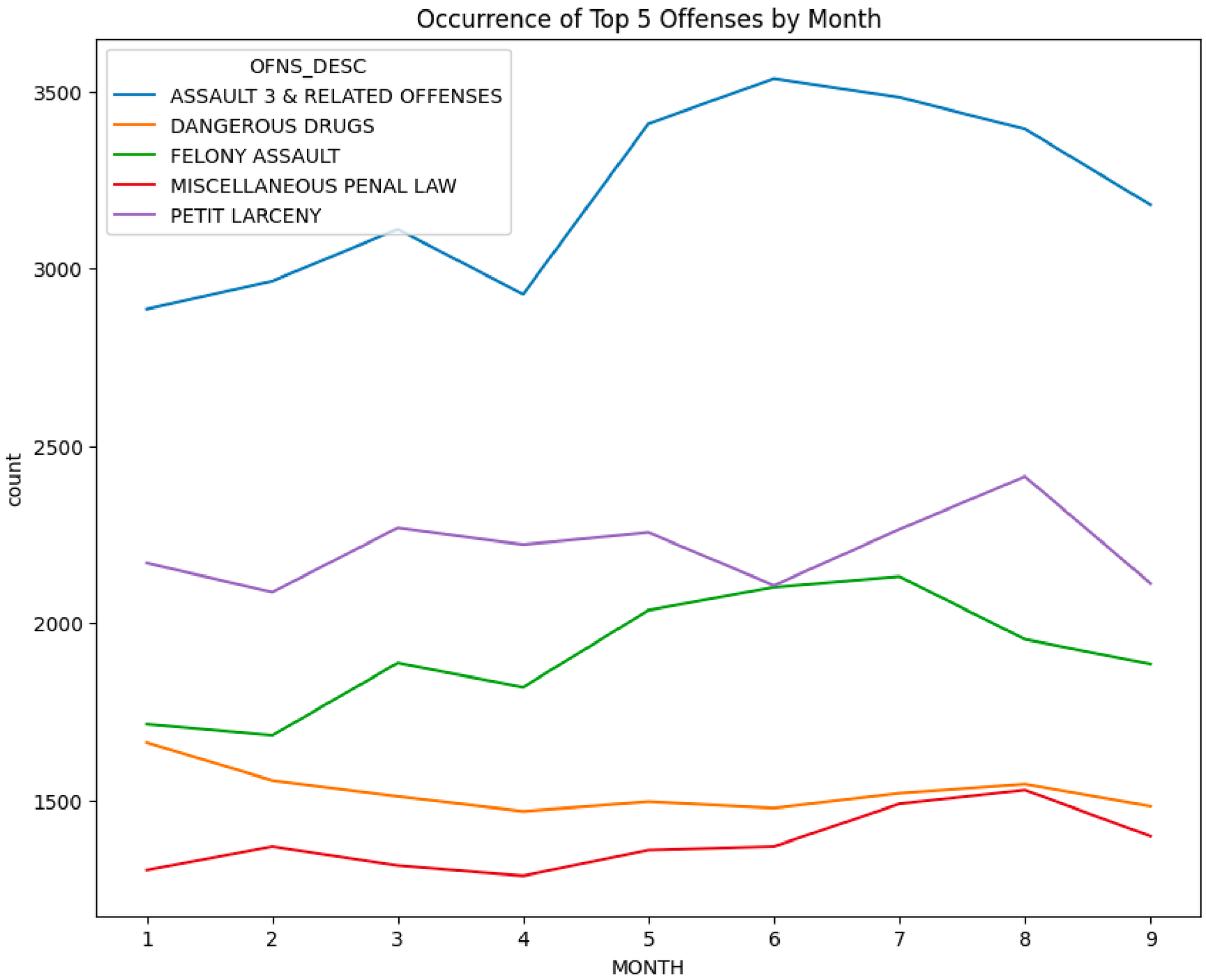
FELONY ASSAULT - F

DRUGS - F

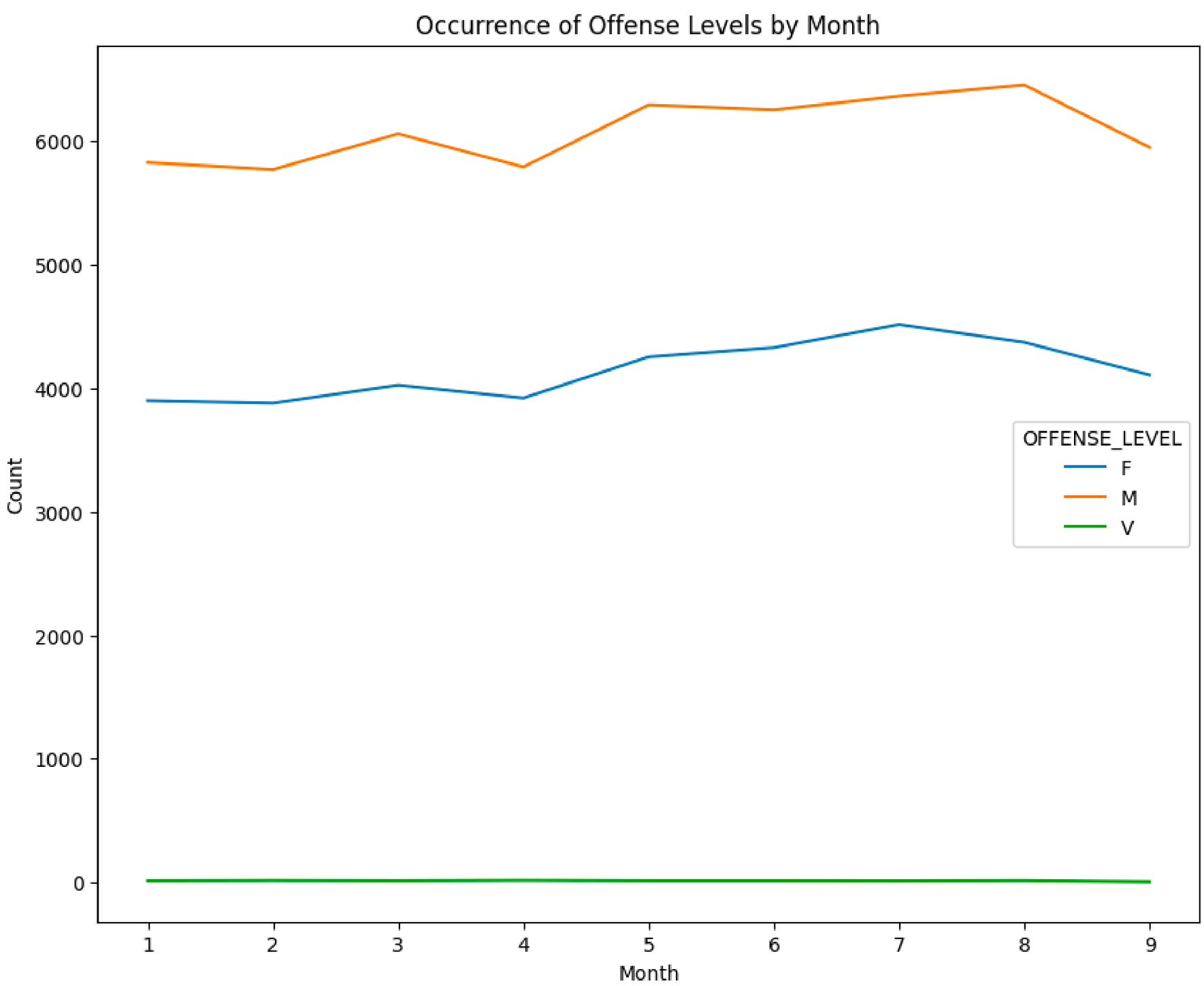
ASSAULT - M

LARCENY - M

MISC - F

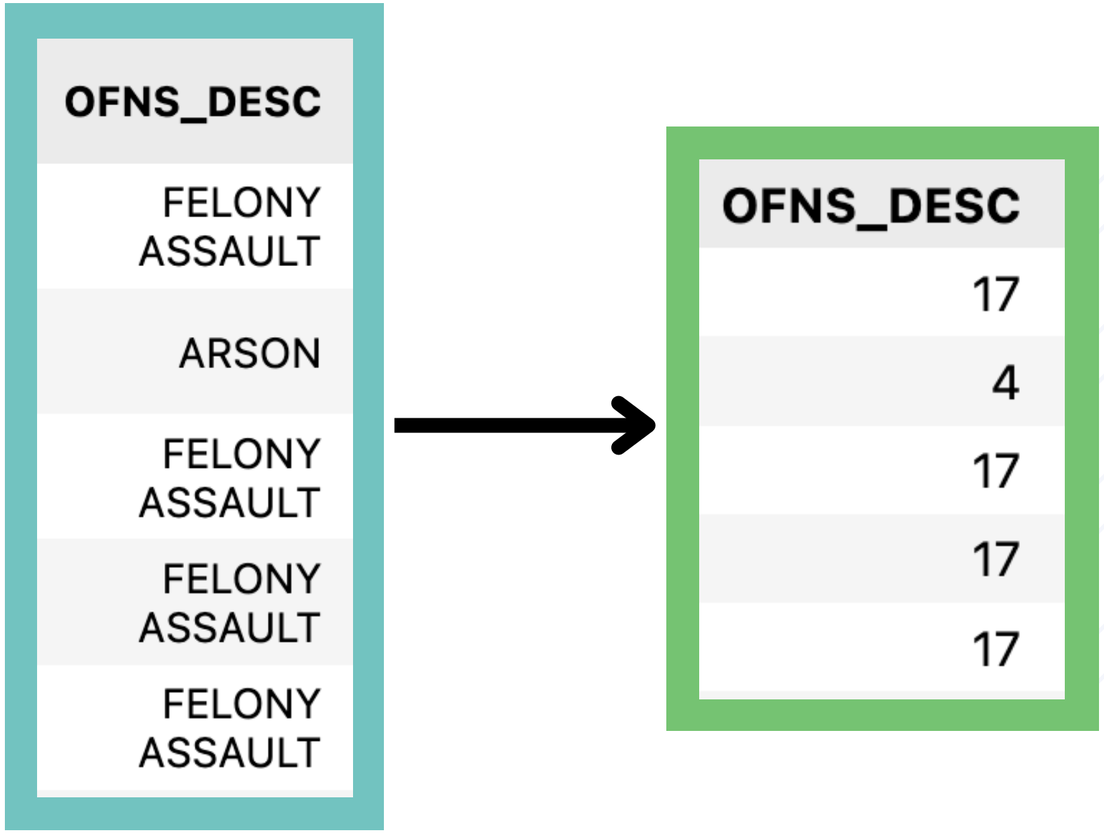


EDA


Occurrence of Offense Levels by Month
Count
6000
5000
4000
3000
2000
1000
0
1
2
3
4
5
6
7
8
9
Month
OFFENSE_LEVEL
F
M
V

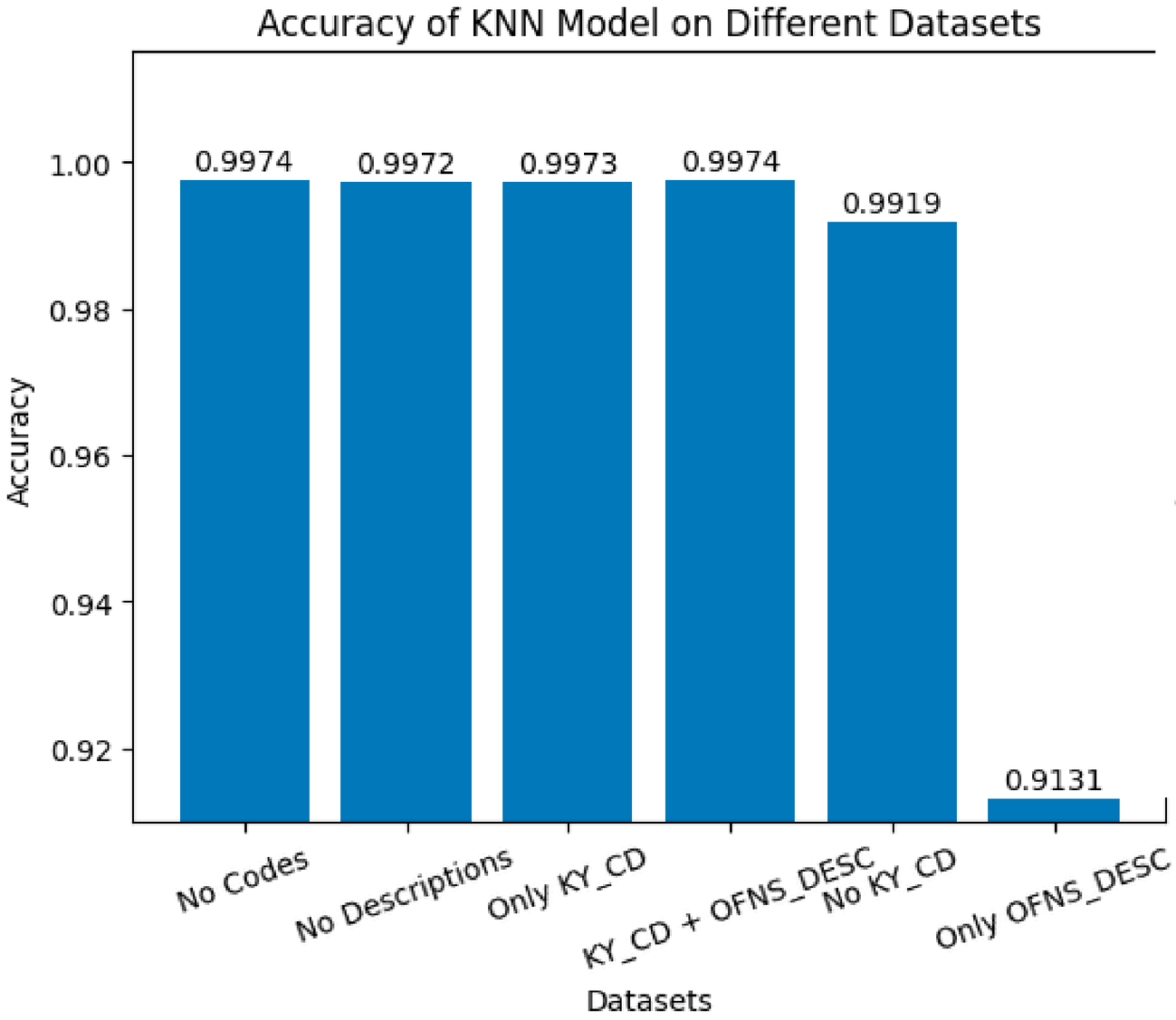
Data Cleaning

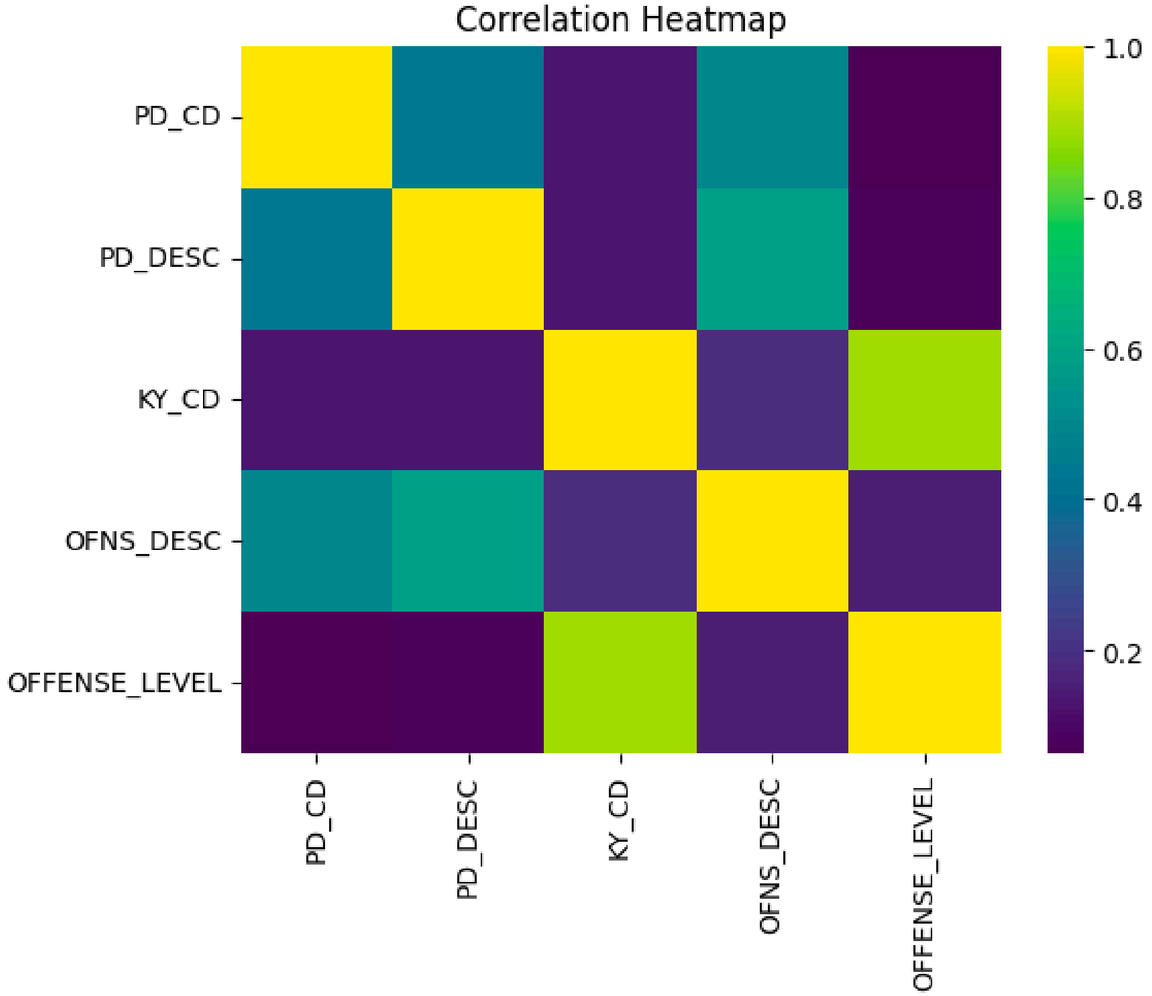
- Dropped null values
- Dropped non-important columns
- Made sure OFFENSE_LEVEL was only M, F, V
- Derived season and month column from date
- Converted code + defense columns to categorical
- Label encode the object columns
  - Label encoding converts categorical data into numerical data
  - might cause priority -- leading to misleading patterns or biases during training



MACHINE LEARNING MODELS

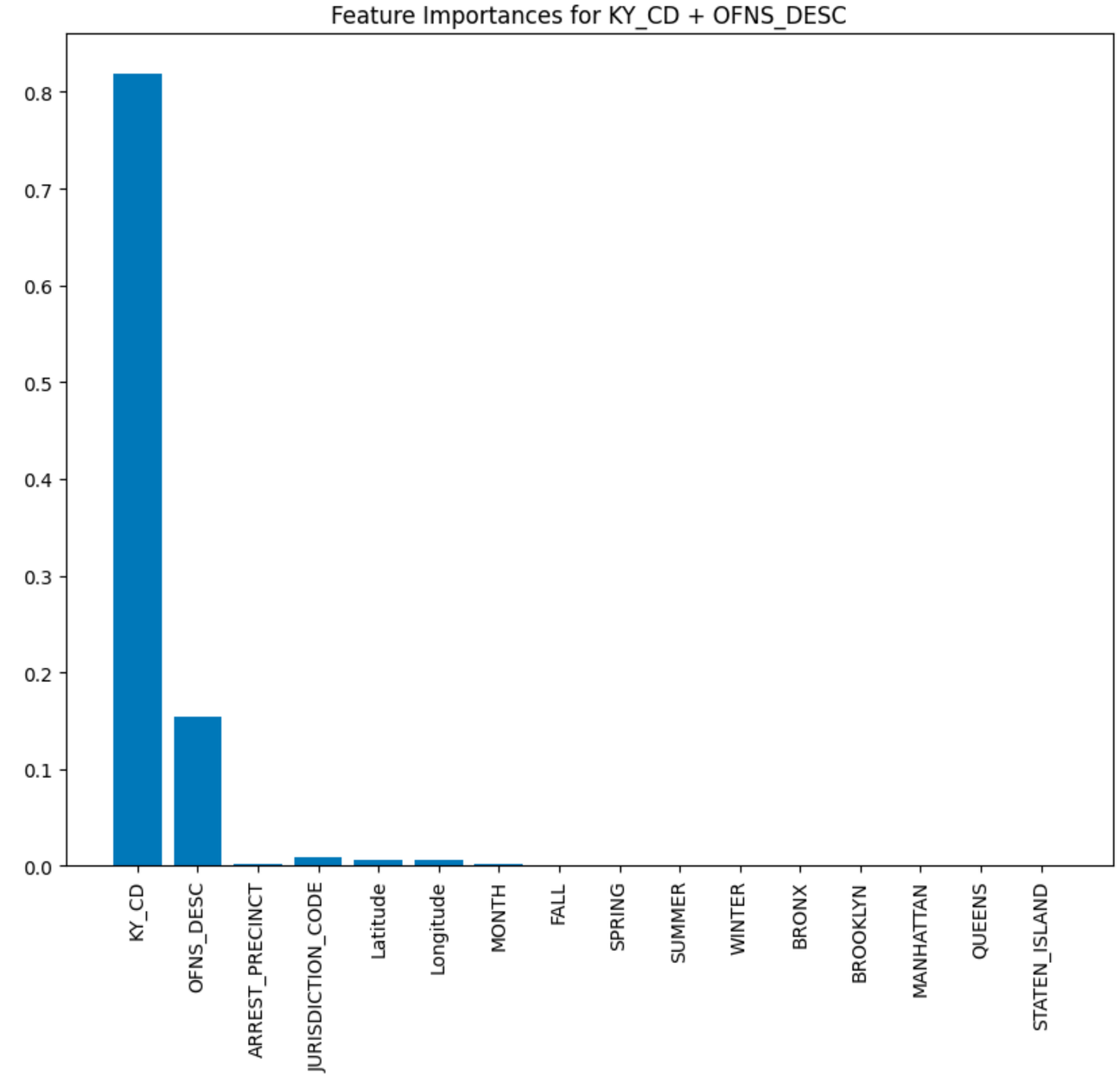
MODELS

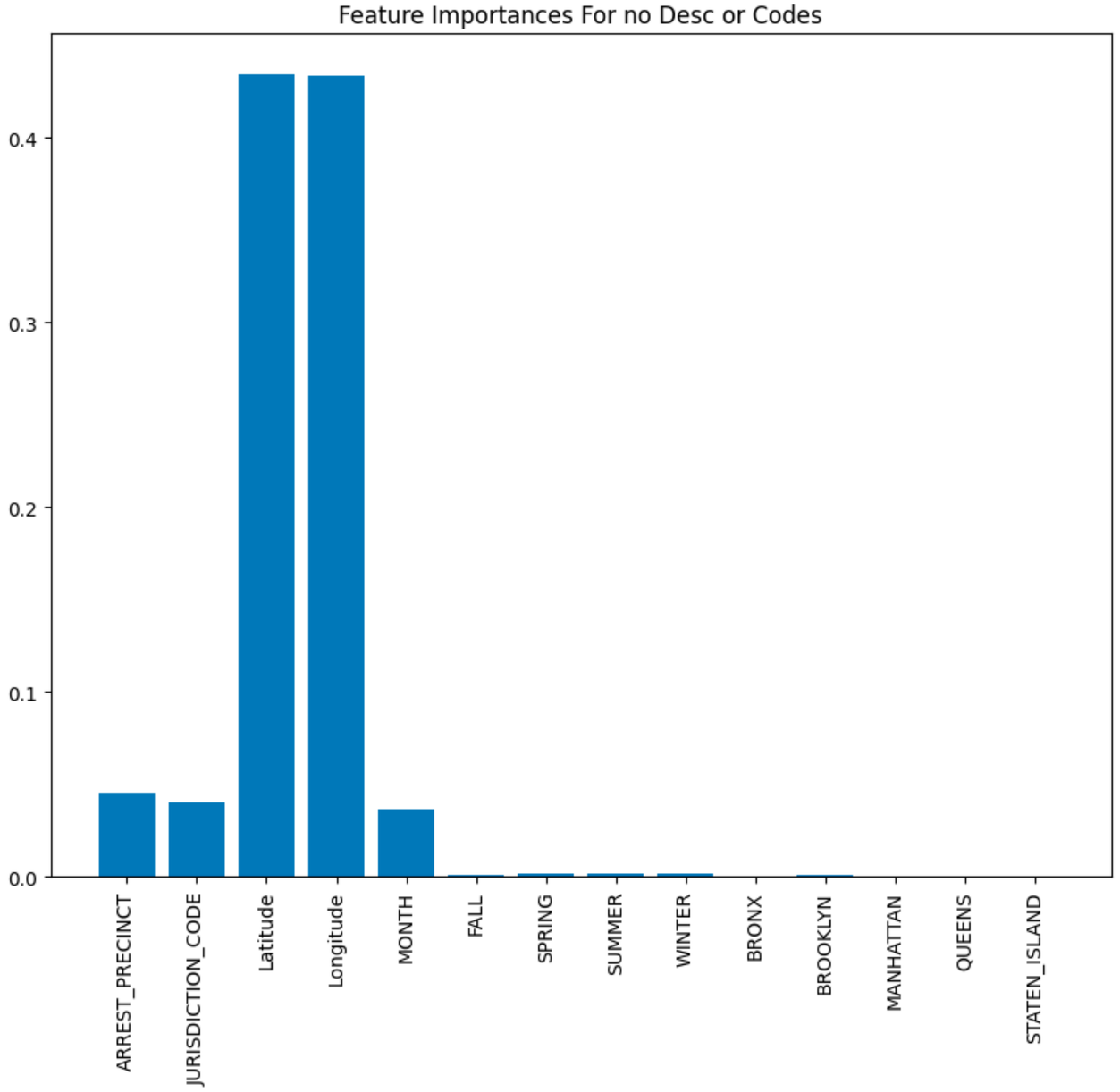




No Codes: 0.9756727441764371
No Descriptions: 0.9972367129797015
No PD CD/DESC: 0.99728836320438
No KY_CD: 0.9918909147254791
KY_CD + OFNS_DESC: 0.9974174887660762
Only OFNS_DESC: 0.9130726718661226
No Codes/Descriptions: 0.6178399876039461

MODELS


Feature Importances for KY_CD + OFNS_DESC
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
KY_CD
OFNS_DESC
ARREST_PRECINCT
JURISDICTION_CODE
Latitude
Longitude
MONTH
FALL
SPRING
SUMMER
WINTER
BRONX
BROOKLYN
MANHATTAN
QUEENS
STATEN_ISLAND

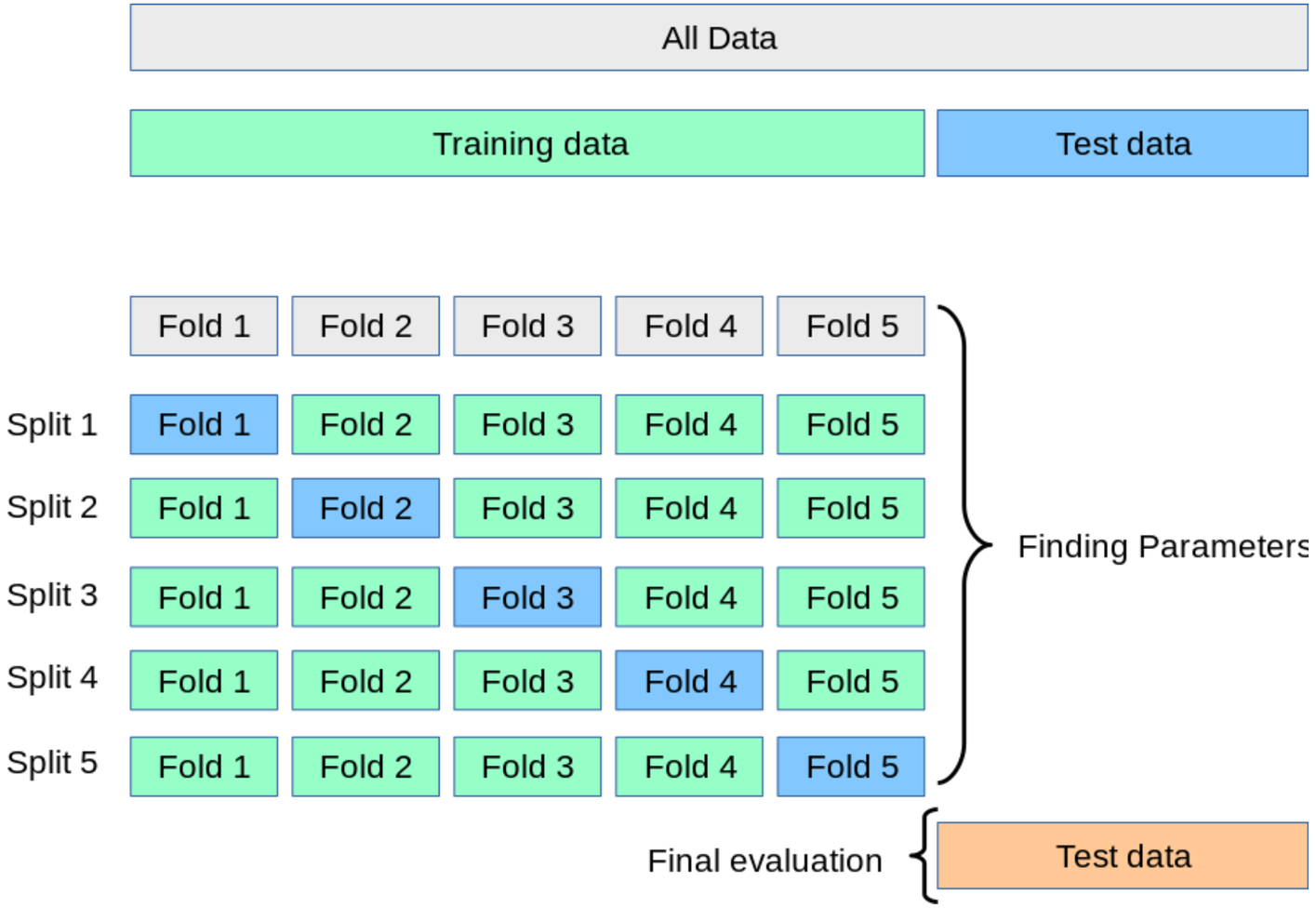

Feature Importances For no Desc or Codes
0.0
0.1
0.2
0.3
0.4
ARREST_PRECINCT
JURISDICTION_CODE
Latitude
Longitude
MONTH
FALL
SPRING
SUMMER
WINTER
BRONX
BROOKLYN
MANHATTAN
QUEENS
STATEN_ISLAND

MODELS

Cross Validation:

Model Evaluation Technique

- Resamples to train model on different iterations
- Compare models
- Avoid Overfitting
- Assess generalization to unseen data
- splitting your dataset into *K* subsets
- Not training the same model

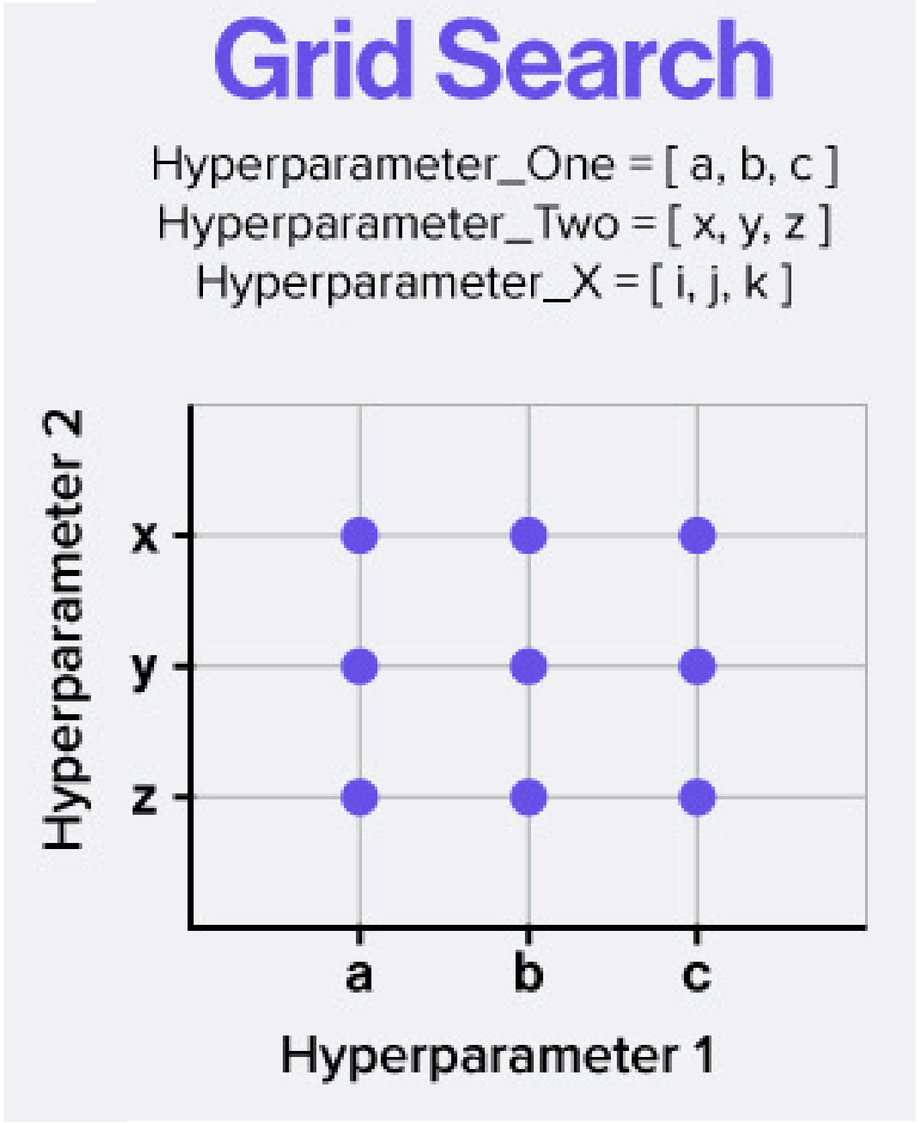


MODELS

Grid Search:

Hyperparameter Tuning Technique

- find the best combo of hyperparameters for a given model
- GridSearchCV()
  - FIRST optimize parameters with Grid Search, SECOND evaluate performance of that model with cross val



MODELS

KNN

	precision	recall	f1-score	support
0	0.902744	0.917254	0.909941	24823
1	0.935837	0.927600	0.931700	32721
2	0.848131	0.673469	0.750776	539
accuracy	0.920820	0.920820	0.920820	0
macro avg	0.895570	0.839441	0.864139	58083
weighted avg	0.920880	0.920820	0.920722	58083

Without Demographics

Best KNN Model: {'metric': 'manhattan', 'n_neighbors': 7, 'weights': 'distance'}

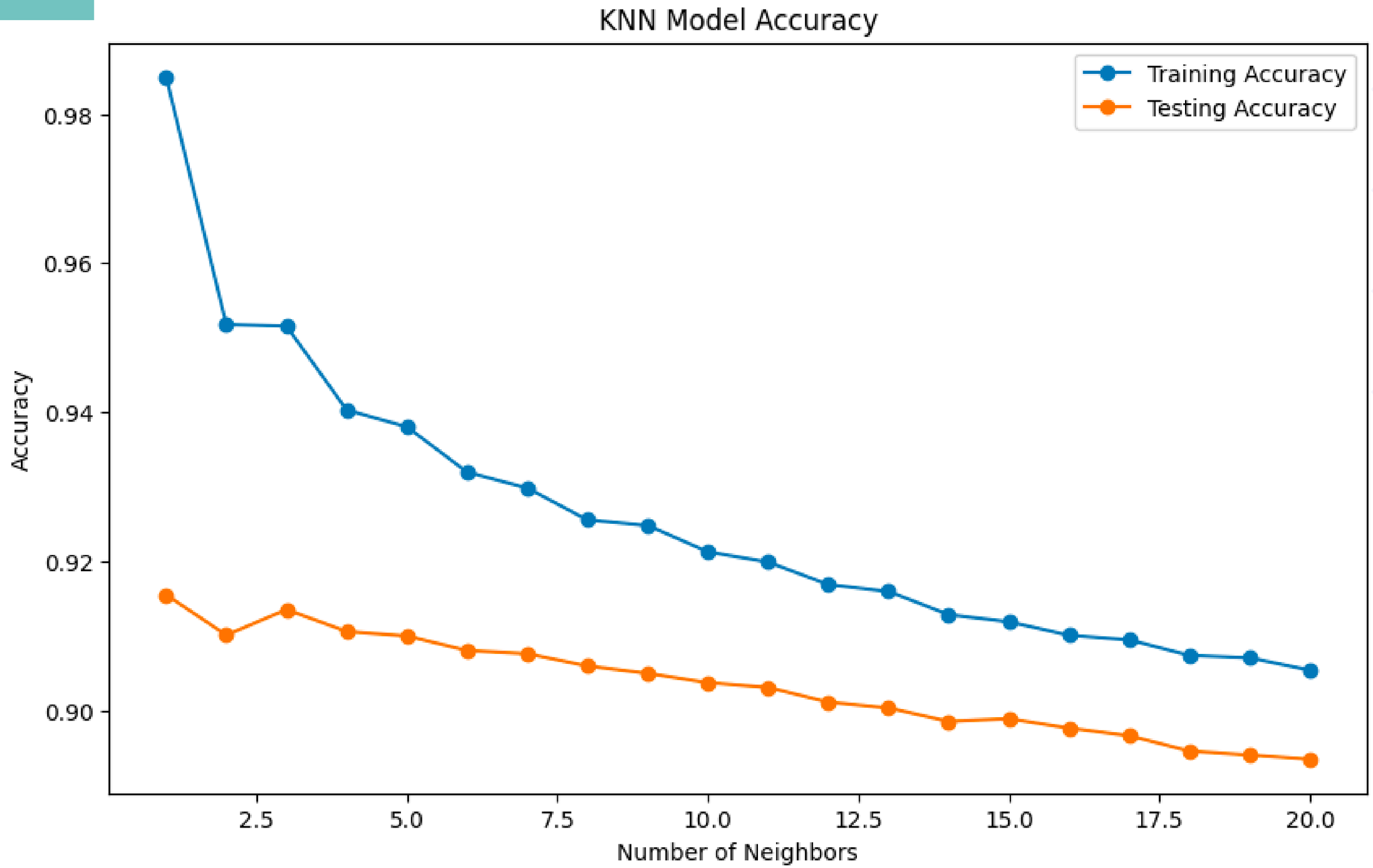
	precision	recall	f1-score	support
0	0.888982	0.894533	0.891749	24823
1	0.915780	0.918187	0.916982	32721
2	0.865772	0.478664	0.616487	539
accuracy	0.903999	0.903999	0.903999	0
macro avg	0.890178	0.763795	0.808406	58083
weighted avg	0.903863	0.903999	0.903410	58083

With Demographics

Best KNN Model: {'metric': 'manhattan', 'n_neighbors': 7, 'weights': 'distance'}

MODELS

KNN


KNN Model Accuracy
Training Accuracy
Testing Accuracy
Accuracy
0.98
0.96
0.94
0.92
0.90
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
Number of Neighbors

MODELS

DECISION TREES (CART)

	precision	recall	f1-score	support
0	0.893831	0.945575	0.918975	24823
1	0.957464	0.916995	0.936793	32721
2	0.944330	0.849722	0.894531	539
accuracy	0.928585	0.928585	0.928585	0
macro avg	0.931875	0.904097	0.916766	58083
weighted avg	0.930147	0.928585	0.928786	58083

Without Demographics

Best Params: {'criterion': 'entropy', 'max_depth': 15, 'min_samples_leaf': 4, 'min_samples_split': 10}

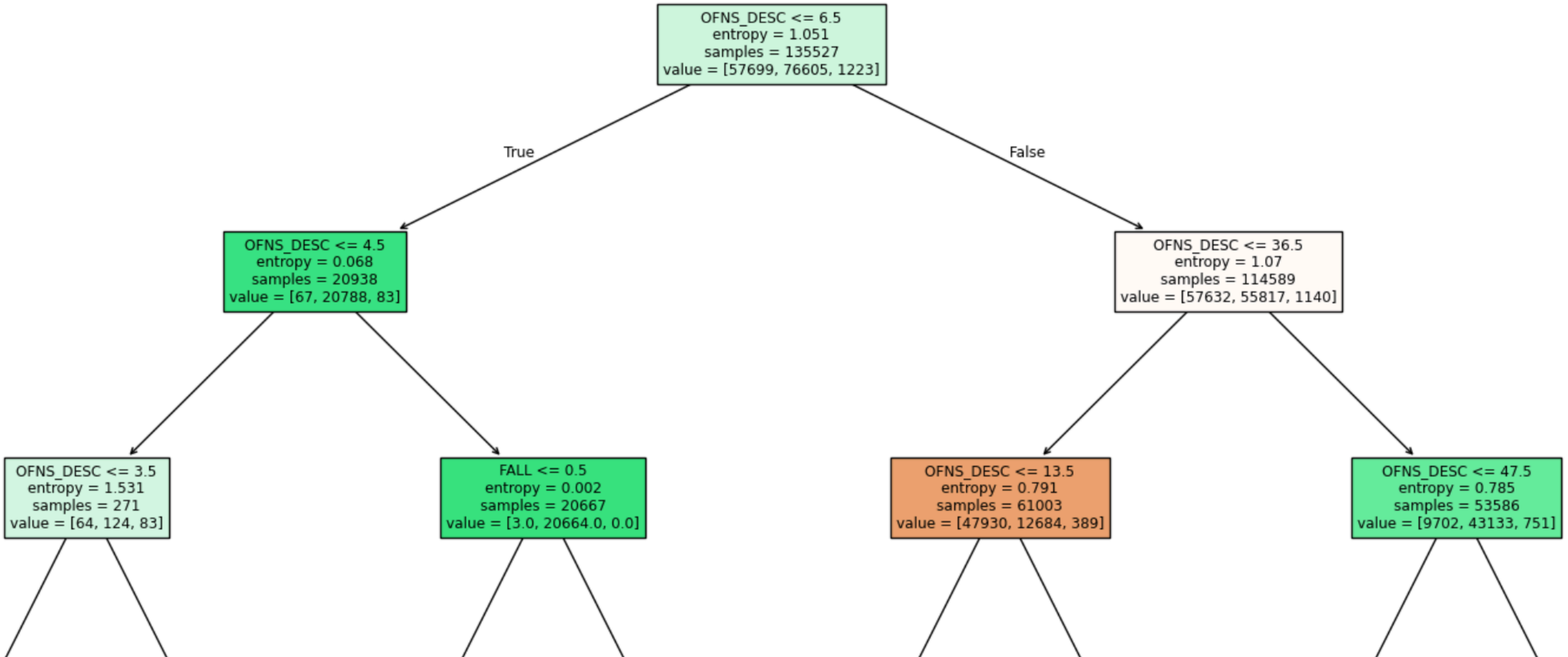
	precision	recall	f1-score	support
0	0.896273	0.938807	0.917047	24823
1	0.952556	0.919776	0.935879	32721
2	0.944559	0.853432	0.896686	539
accuracy	0.927294	0.927294	0.927294	0
macro avg	0.931129	0.904005	0.916537	58083
weighted avg	0.928428	0.927294	0.927467	58083

With Demographics

Best Params: {'criterion': 'entropy', 'max_depth': 15, 'min_samples_leaf': 4, 'min_samples_split': 10}

MODELS

DECISION TREES (CART)



MODELS

SVM

	precision	recall	f1-score	support
0	0.679851	0.762398	0.718762	24823
1	0.793659	0.733627	0.762463	32721
2	0.000000	0.000000	0.000000	539
accuracy	0.739115	0.739115	0.739115	0
macro avg	0.491170	0.498675	0.493742	58083
weighted avg	0.737655	0.739115	0.736711	58083

Without Demographics

Default Params: {'C': 1.0, 'kernel': 'rbf', 'gamma': 'scale'}

	precision	recall	f1-score	support
0	0.679795	0.762801	0.718910	24823
1	0.793873	0.733413	0.762446	32721
2	0.000000	0.000000	0.000000	539
accuracy	0.739166	0.739166	0.739166	0
macro avg	0.491223	0.498738	0.493785	58083
weighted avg	0.737752	0.739166	0.736765	58083

With Demographics

Default Params: {'C': 1.0, 'kernel': 'rbf', 'gamma': 'scale'}

MODELS

LINEAR SVM

	precision	recall	f1-score	support
0	0.273829	0.144664	0.189314	24823
1	0.516623	0.710003	0.598069	32721
2	0.000000	0.000000	0.000000	539
accuracy	0.461805	0.461805	0.461805	0
macro avg	0.263484	0.284889	0.262461	58083
weighted avg	0.408066	0.461805	0.417829	58083

Without Demographics

Default Params: {'C': 1.0, 'kernel': 'linear', 'gamma': 'scale'}

	precision	recall	f1-score	support
0	0.477977	0.265802	0.341626	24823
1	0.577023	0.780844	0.663636	32721
2	0.000000	0.000000	0.000000	539
accuracy	0.553484	0.553484	0.553484	0
macro avg	0.351667	0.348882	0.335088	58083
weighted avg	0.529339	0.553484	0.519860	58083

With Demographics

Default Params: {'C': 1.0, 'kernel': 'linear', 'gamma': 'scale'}

MODELS

LOGISTIC REGRESSION

	precision	recall	f1-score	support
0	0.282136	0.150667	0.196434	24823
1	0.518415	0.710217	0.599345	32721
2	0.000000	0.000000	0.000000	539
accuracy	0.464490	0.464490	0.464490	0
macro avg	0.266851	0.286961	0.265260	58083
weighted avg	0.412626	0.464490	0.421590	58083

Without Demographics

Best Params: {'max_iter': 1000, 'solver': 'liblinear'}

	precision	recall	f1-score	support
0	0.478397	0.271200	0.346163	24823
1	0.577515	0.776779	0.662488	32721
2	0.000000	0.000000	0.000000	539
accuracy	0.553501	0.553501	0.553501	0
macro avg	0.351971	0.349327	0.336217	58083
weighted avg	0.529795	0.553501	0.521152	58083

With Demographics

Best Params: {'max_iter': 1000, 'solver': 'liblinear'}

MODELS

NAIVE BAYES

	precision	recall	f1-score	support
0	0.532478	0.466301	0.497197	24823
1	0.621984	0.690871	0.654620	32721
2	0.000000	0.000000	0.000000	539
accuracy	0.588485	0.588485	0.588485	0
macro avg	0.384820	0.385724	0.383939	58083
weighted avg	0.577960	0.588485	0.581267	58083

Without Demographics

Mixed NB, For categorial/Numeric

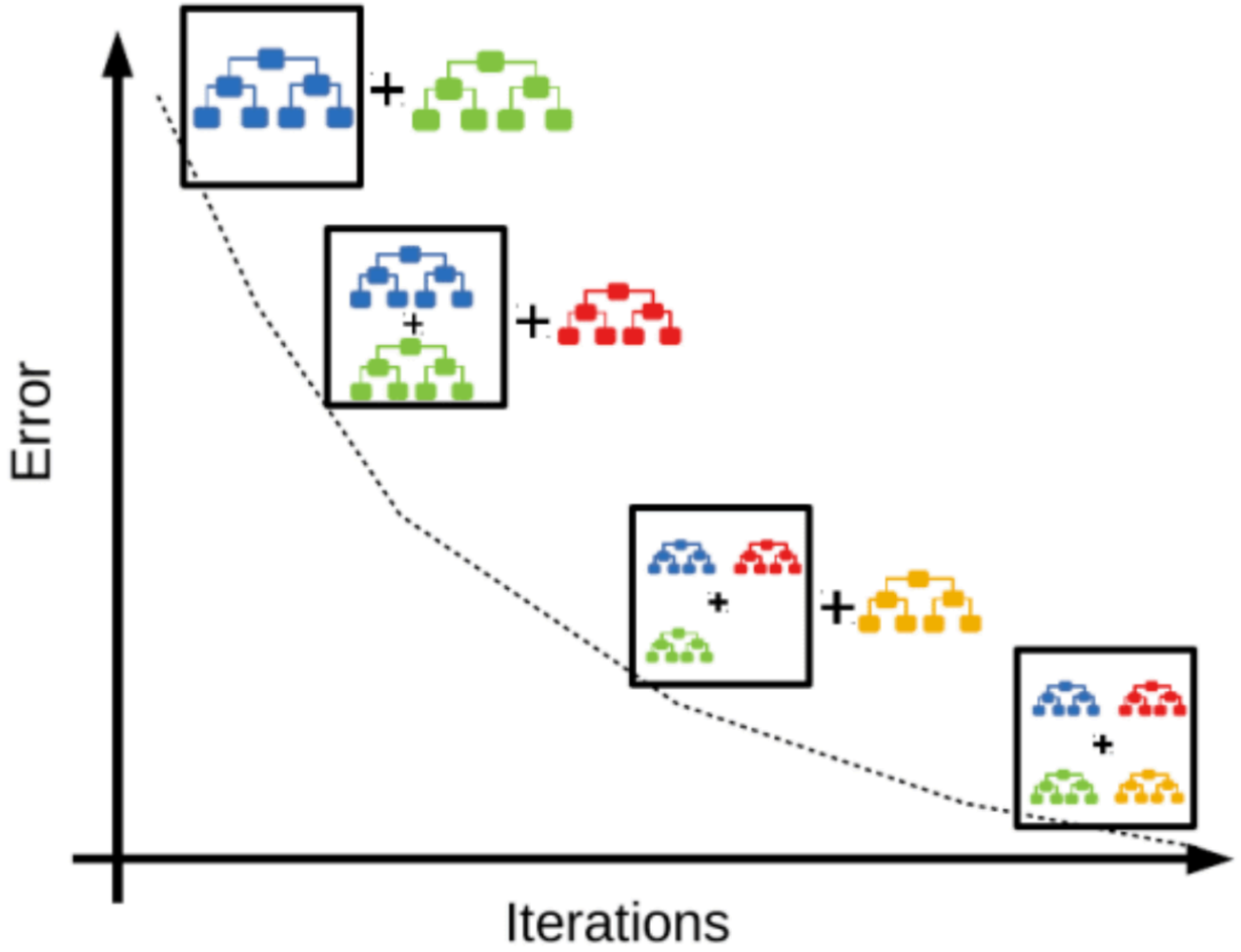
	precision	recall	f1-score	support
0	0.572105	0.428474	0.489980	24823
1	0.628862	0.758993	0.687826	32721
2	0.000000	0.000000	0.000000	539
accuracy	0.610695	0.610695	0.610695	0
macro avg	0.400322	0.395822	0.392602	58083
weighted avg	0.598770	0.610695	0.596890	58083

With Demographics

Mixed NB, For categorial/Numeric

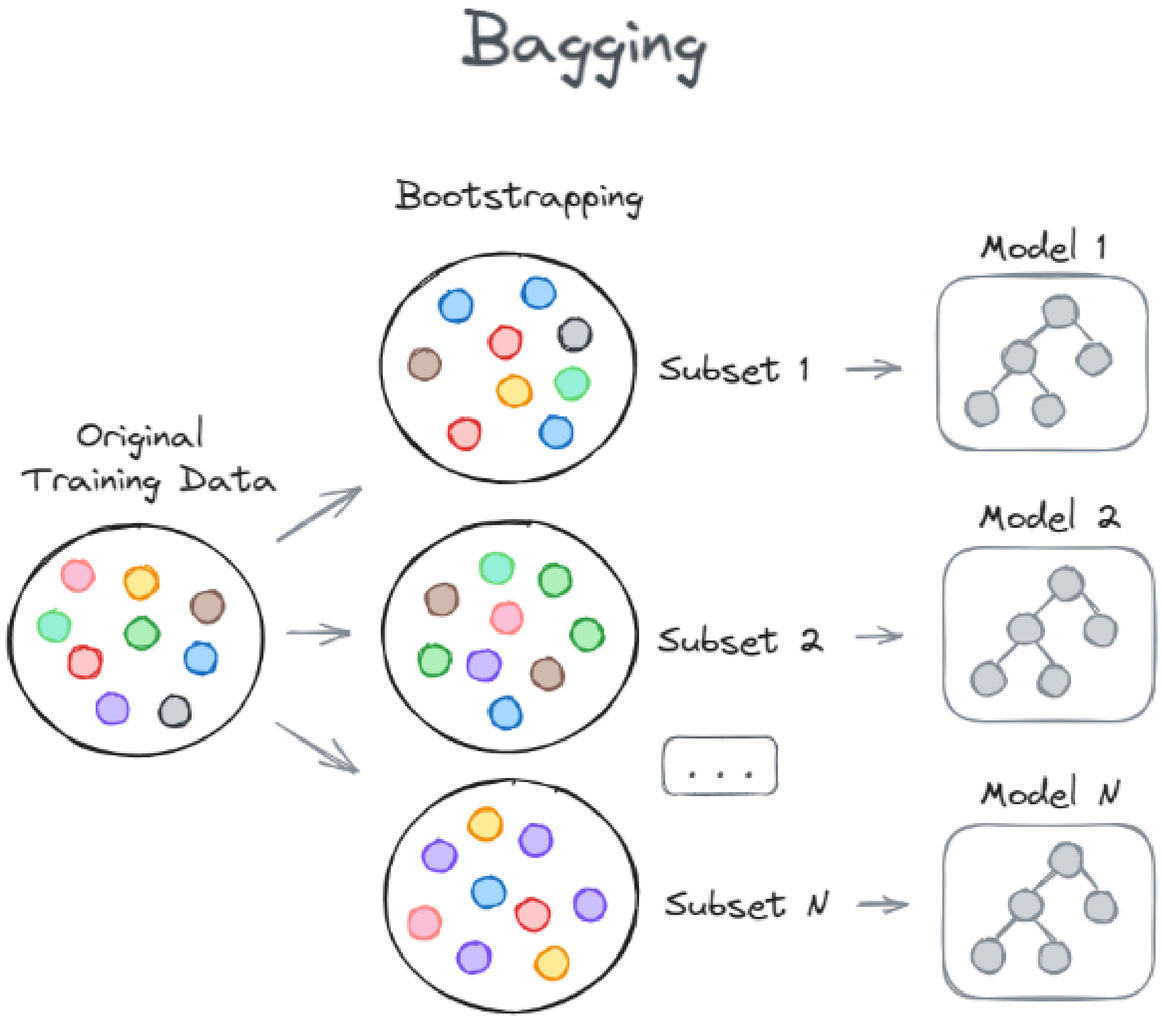
ENSEMBLE MODELS

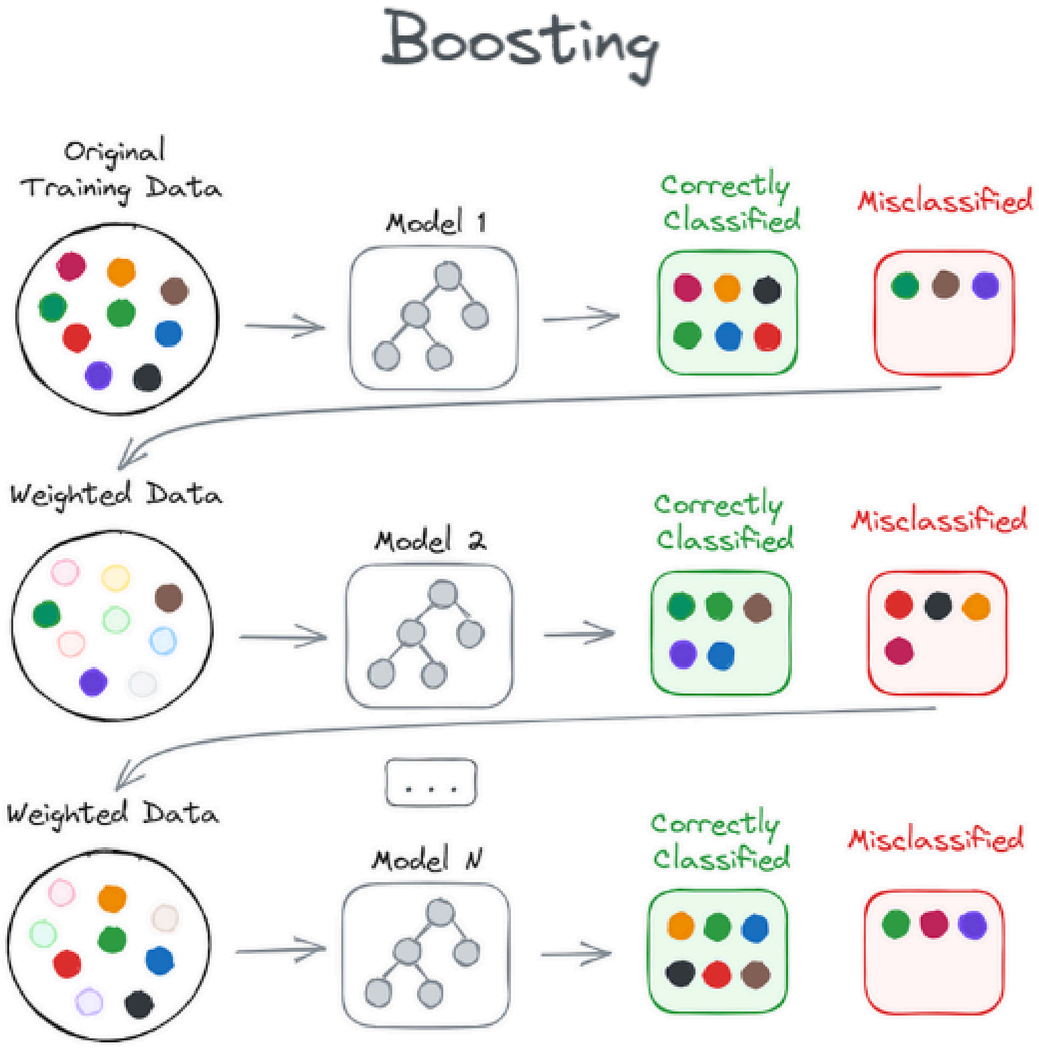
- combine the predictions of multiple individual models (weak learners) to improve the overall performance
  - reduce overfitting
  - different errors, can cancel out
  - more robust
- Bagging
- Boosting



MODELS

BAGGING (BOOTSTRAP) VS BOOSTING





MODELS

RANDOM FOREST

	precision	recall	f1-score	support
0	0.889875	0.924828	0.907015	24823
1	0.940086	0.915895	0.927833	32721
2	0.970443	0.730983	0.833862	539
accuracy	0.917997	0.917997	0.917997	0
macro avg	0.933468	0.857235	0.889570	58083
weighted avg	0.918909	0.917997	0.918064	58083

	precision	recall	f1-score	support
0	0.874675	0.920799	0.897145	24823
1	0.935389	0.903029	0.918924	32721
2	0.988950	0.664193	0.794673	539
accuracy	0.908407	0.908407	0.908407	0
macro avg	0.933005	0.829340	0.870247	58083
weighted avg	0.909938	0.908407	0.908463	58083

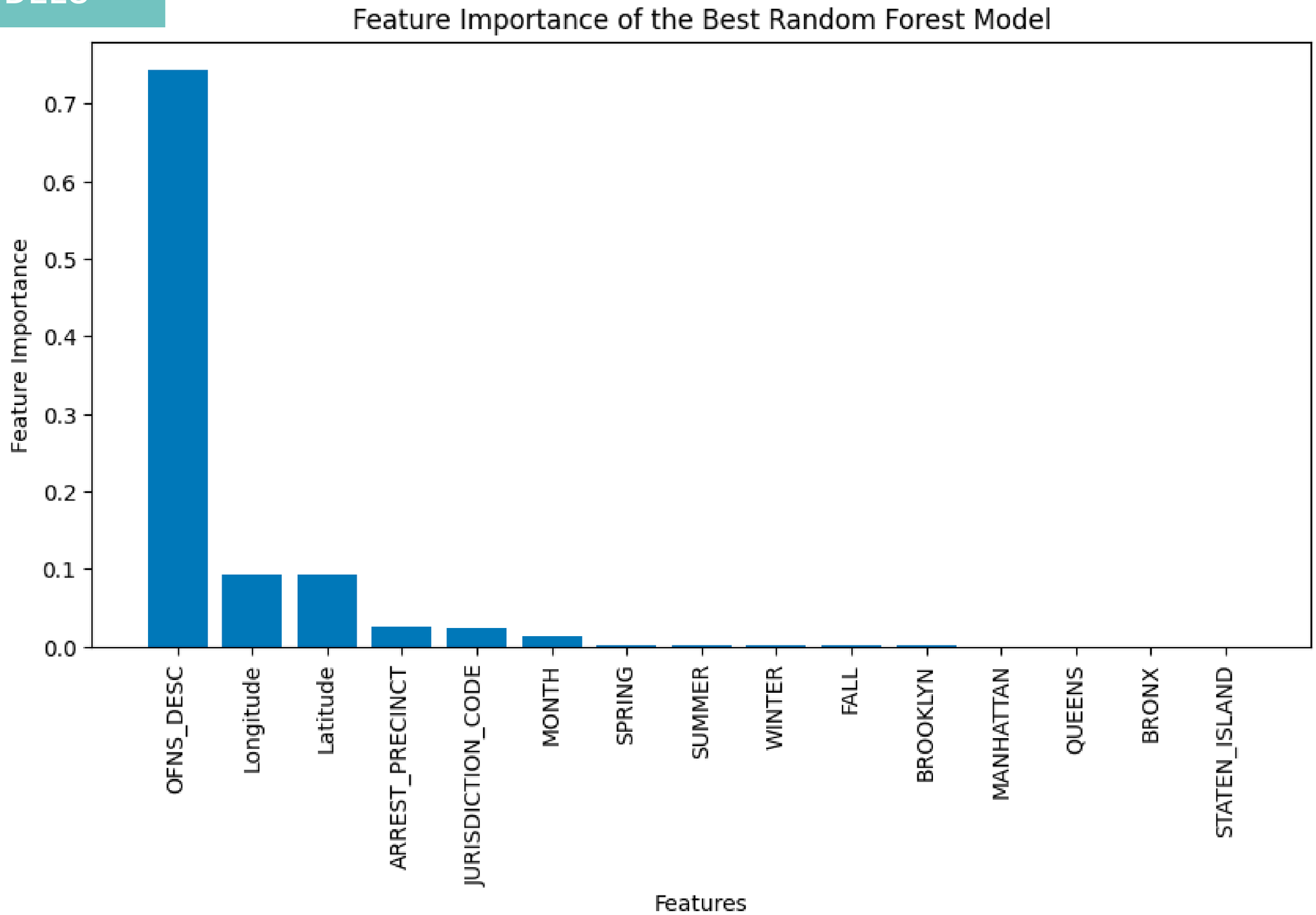
Without Demographics

Best parameters for Random Forest:
{'max_depth': 30, 'min_samples_leaf': 1,
'min_samples_split': 5, 'n_estimators': 200}

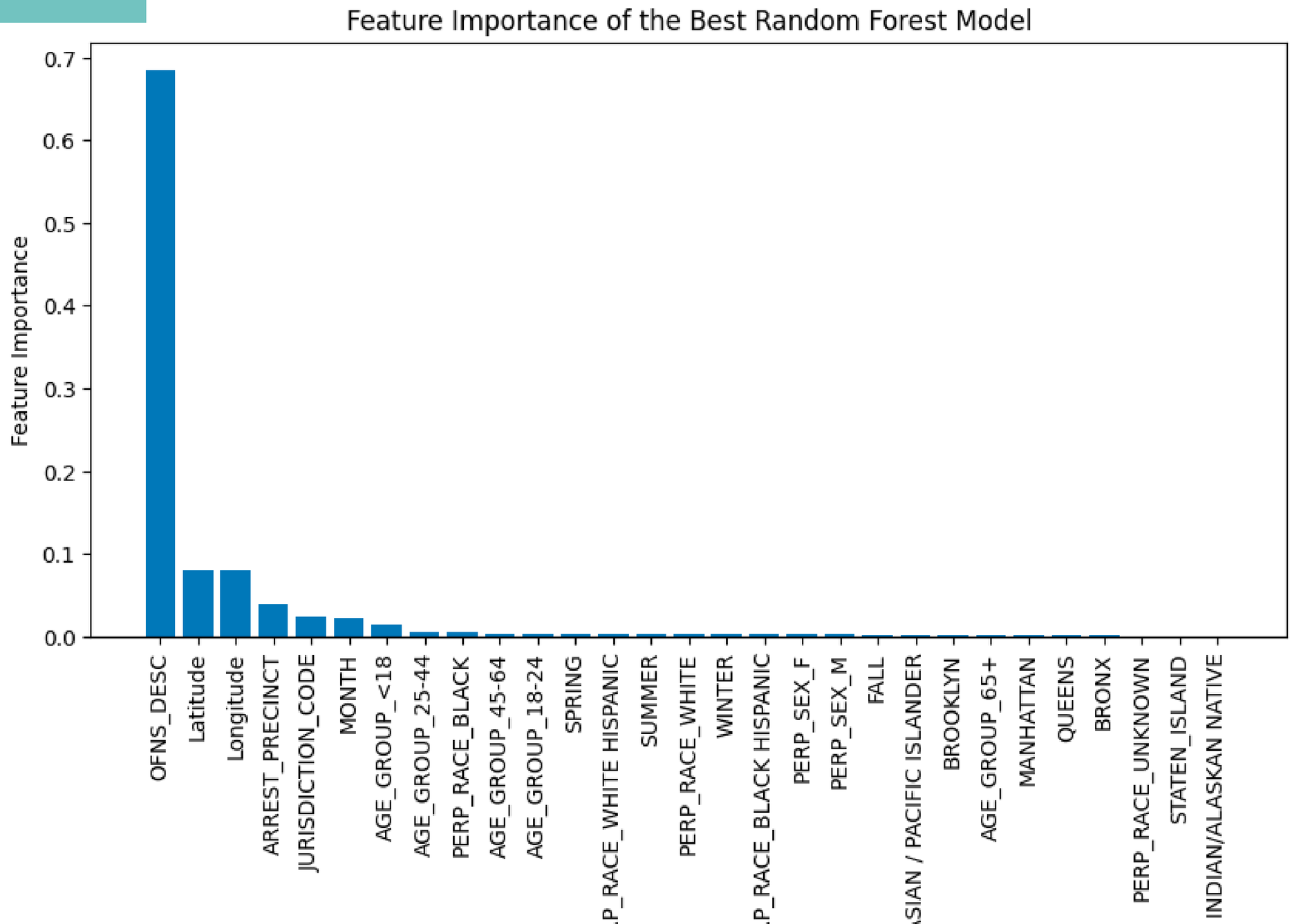
With Demographics

Best parameters for Random Forest:
{'max_depth': 40, 'min_samples_leaf': 1,
'min_samples_split': 5, 'n_estimators': 300}

MODELS


Feature Importance of the Best Random Forest Model
Feature Importance
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
OFNS_DESC
Longitude
Latitude
ARREST_PRECINCT
JURISDICTION_CODE
MONTH
SPRING
SUMMER
WINTER
FALL
BROOKLYN
MANHATTAN
QUEENS
BRONX
STATEN_ISLAND
Features

MODELS


Feature Importance of the Best Random Forest Model
Feature Importance
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
OFNS_DESC
Latitude
Longitude
ARREST_PRECINCT
JURISDICTION_CODE
MONTH
AGE_GROUP_<18
AGE_GROUP_25-44
PERP_RACE_BLACK
AGE_GROUP_45-64
AGE_GROUP_18-24
SPRING
P_RACE_WHITE HISPANIC
SUMMER
PERP_RACE_WHITE
WINTER
P_RACE_BLACK HISPANIC
PERP_SEX_F
PERP_SEX_M
FALL
SIAN / PACIFIC ISLANDER
BROOKLYN
AGE_GROUP_65+
MANHATTAN
QUEENS
BRONX
PERP_RACE_UNKNOWN
STATEN_ISLAND
INDIAN/ALASKAN NATIVE

MODELS

GRADIENT CLASSIFIER

	precision	recall	f1-score	support
0	0.894910	0.950610	0.921920	24823
1	0.961180	0.917117	0.938632	32721
2	0.943320	0.864564	0.902227	539
accuracy	0.930944	0.930944	0.930944	0
macro avg	0.933137	0.910764	0.920926	58083
weighted avg	0.932693	0.930944	0.931152	58083

Without Demographics

Best parameters for Gradient Clasifier :
{'learning_rate': 0.1, 'max_depth': 5,
'min_samples_leaf': 1, 'n_estimators': 300}

	precision	recall	f1-score	support
0	0.904030	0.947951	0.925470	24823
1	0.959361	0.925644	0.942201	32721
2	0.962733	0.862709	0.909980	539
accuracy	0.934594	0.934594	0.934594	0
macro avg	0.942041	0.912101	0.925884	58083
weighted avg	0.935746	0.934594	0.934752	58083

With Demographics

Best parameters for Gradient Classifier:
{'learning_rate': 0.1, 'max_depth': 5,
'min_samples_leaf': 4, 'n_estimators': 300}

MODELS

HISTOGRAM GRADIENT

	precision	recall	f1-score	support
0	0.887117	0.958949	0.921635	24823
1	0.967552	0.909477	0.937616	32721
2	0.935091	0.855288	0.893411	539
accuracy	0.930117	0.930117	0.930117	0
macro avg	0.929920	0.907905	0.917554	58083
weighted avg	0.932875	0.930117	0.930376	58083

Without Demographics

Best parameters: {'l2_regularization': 0.1, 'learning_rate': 0.1, 'max_depth': 7}

	precision	recall	f1-score	support
0	0.903500	0.946340	0.924424	24823
1	0.958469	0.925369	0.941628	32721
2	0.941057	0.858998	0.898157	539
accuracy	0.933716	0.933716	0.933716	0
macro avg	0.934342	0.910236	0.921403	58083
weighted avg	0.934815	0.933716	0.933872	58083

With Demographics

Best parameters: {'l2_regularization': 0.1, 'learning_rate': 0.1, 'max_depth': 7}

MODELS

BAGGING CLASSIFIER

	precision	recall	f1-score	support
0	0.913929	0.934657	0.924177	24823
1	0.950166	0.935240	0.942644	32721
2	0.951020	0.864564	0.905734	539
accuracy	0.934335	0.934335	0.934335	0
macro avg	0.938372	0.911487	0.924185	58083
weighted avg	0.934687	0.934335	0.934409	58083

Without Demographics

Best parameters: {'max_samples': 0.5, 'n_estimators': 400}

	precision	recall	f1-score	support
0	0.912496	0.936390	0.924288	24823
1	0.951232	0.934110	0.942593	32721
2	0.964435	0.855288	0.906588	539
accuracy	0.934353	0.934353	0.934353	0
macro avg	0.942721	0.908596	0.924490	58083
weighted avg	0.934800	0.934353	0.934436	58083

With Demographics

Best parameters: {'max_samples': 0.5, 'n_estimators': 400}

MODELS

XGBOOST

	precision	recall	f1-score	support
0	0.899332	0.944366	0.921299	24823
1	0.956467	0.921916	0.938873	32721
2	0.964435	0.855288	0.906588	539
accuracy	0.930892	0.930892	0.930892	0
macro avg	0.940078	0.907190	0.922254	58083
weighted avg	0.932123	0.930892	0.931063	58083

Without Demographics

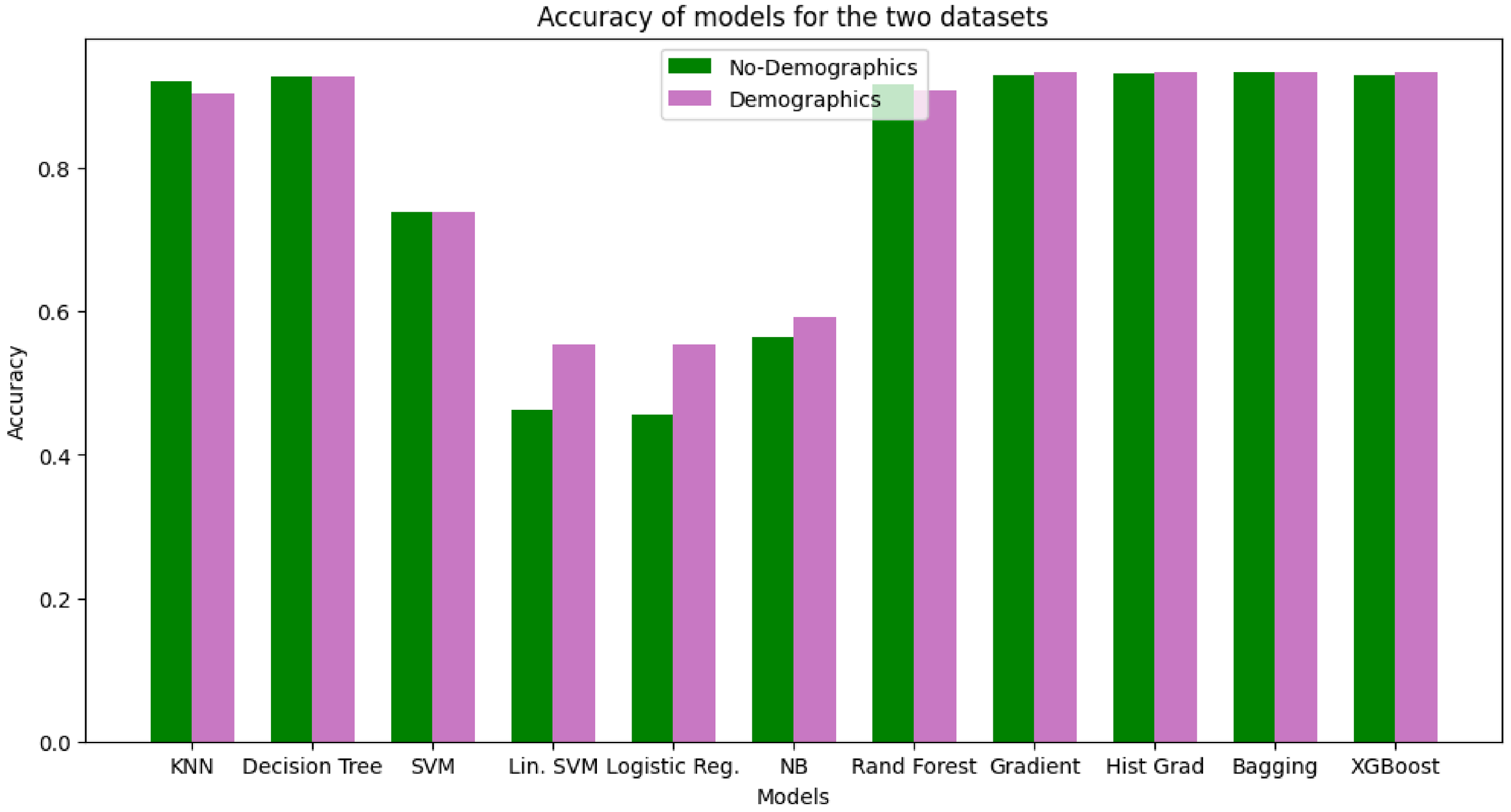
Best parameters: {'max_depth': 4,
'n_estimators': 300}

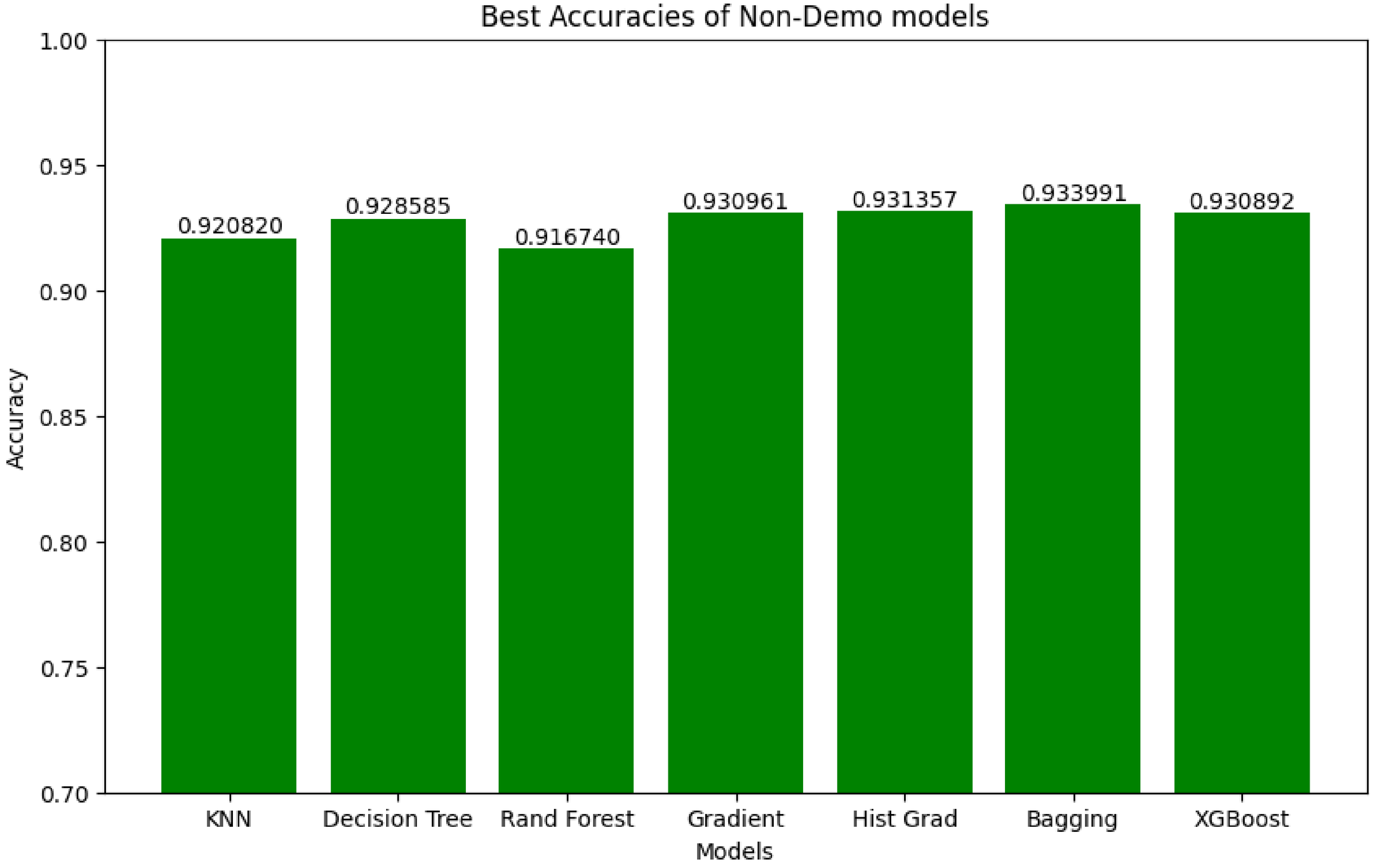
	precision	recall	f1-score	support
0	0.905841	0.944084	0.924567	24823
1	0.956514	0.927661	0.941866	32721
2	0.966527	0.857143	0.908555	539
accuracy	0.934025	0.934025	0.934025	0
macro avg	0.942960	0.909629	0.924996	58083
weighted avg	0.934950	0.934025	0.934164	58083

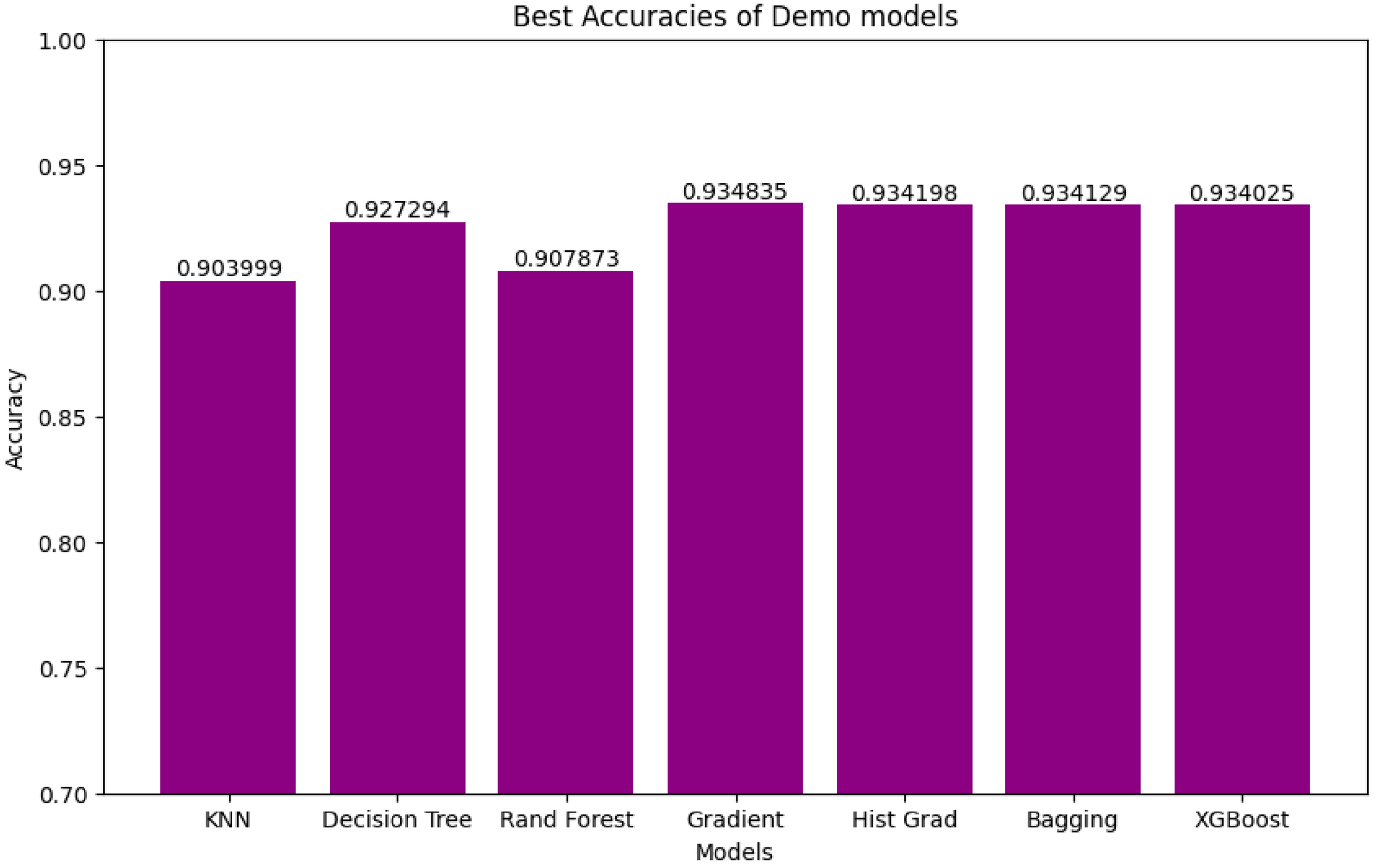
With Demographics

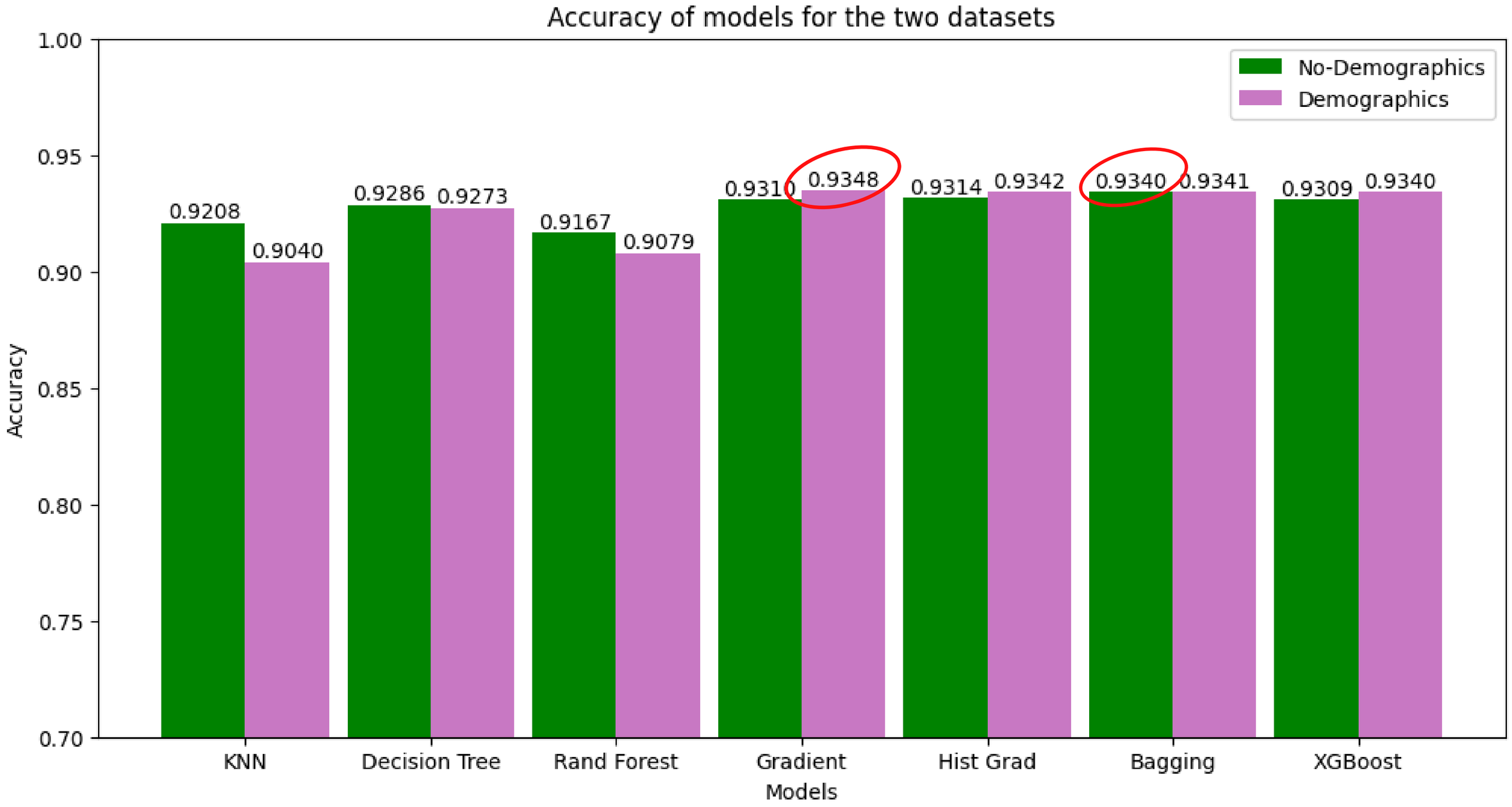
Best parameters: {'max_depth': 5,
'n_estimators': 200}

CONCLUSIONS + TAKEAWAYS


Accuracy of models for the two datasets
No-Demographics
Demographics
Accuracy
0.0
0.2
0.4
0.6
0.8
KNN
Decision Tree
SVM
Lin. SVM
Logistic Reg.
NB
Rand Forest
Gradient
Hist Grad
Bagging
XGBoost
Models


Best Accuracies of Non-Demo models
1.00
0.95
0.90
0.85
0.80
0.75
0.70
Accuracy
0.920820
0.928585
0.916740
0.930961
0.931357
0.933991
0.930892
KNN
Decision Tree
Rand Forest
Gradient
Hist Grad
Bagging
XGBoost
Models


Best Accuracies of Demo models
1.00
0.95
0.90
0.85
0.80
0.75
0.70
Accuracy
0.903999
0.927294
0.907873
0.934835
0.934198
0.934129
0.934025
KNN
Decision Tree
Rand Forest
Gradient
Hist Grad
Bagging
XGBoost
Models


Accuracy of models for the two datasets
No-Demographics
Demographics
1.00
0.95
0.90
0.85
0.80
0.75
0.70
Accuracy
0.9208
0.9040
0.9286
0.9273
0.9167
0.9079
0.9310
0.9348
0.9314
0.9342
0.9340
0.9341
0.9309
0.9340
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CONCLUSION

- Geography matters more than time of year, although there seems to be a spike in all crimes in Spring/Summer
- Models with demographic data are generally less accurate than models without demographic data
- Higher risk areas are identified allowing for better resource allocation to combat crime
- Offenses grouped together as “miscellaneous” warrant further attention from authorities

THANK YOU